The Dissertation Committee for Sai Krishna Yayavaram certifies that this is the approved version of the following dissertation:

Structure of a firm's knowledge base and the effectiveness of technological search

Committee:

James W. Fredrickson, Co-Supervisor

Gautam Ahuja, Co-Supervisor

George P. Huber

Douglas Morrice

Andrew Henderson

Structure of a firm's knowledge base and the effectiveness of technological search

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Sai Krishna Yayavaram, B.Tech

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To Salila, Siddharth and Arnav

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Structure of a firm's knowledge base and the effectiveness of technological search

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Sai Krishna Yayavaram, Ph.D.

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Supervisors: James W. Fredrickson and Gautam Ahuja

This dissertation examines the impact of coupling that exists between the knowledge elements of a firm (i.e., the structure of the firm's knowledge base) on the firm's technological search activity. I define coupling as the decision made on how the search across two knowledge elements should be combined and distinguish it from interdependence, which is the inherent relationship between these two elements. I ask two questions: 1) How does the structure of a firm's knowledge base impact the usefulness of a firm's inventions? 2) How does the prior structure of a firm's knowledge base affect the malleability of the knowledge base? Malleability is defined as the capacity for adaptive change.

Inventions are generated when existing knowledge elements are combined in novel ways. Given the large number of potential combinations of knowledge elements, the problem of searching for technological inventions is computationally intractable. I use the NK model to study this computationally complex problem and argue that the structure of a knowledge base can mitigate the negative effects of complexity. In the first part of the dissertation, I show through computer simulations that a structure that is nearly decomposable (i.e. high coupling within a cluster of elements along with low coupling across clusters) increases the effectiveness of search on an NK landscape. In the second part of the dissertation, I test the relationship between near decomposability in the structure of a knowledge base and technology search in the context of the worldwide semiconductor industry. I find support for the hypothesis that a nearly decomposable structure improves the search for technological inventions. Further, I also find support for the hypothesis that firms with a nearly decomposable structure are likely to undergo a larger change in their knowledge base over time.

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GLOSSARY

System	A collection of interacting nodes or elements or components or very broadly, decisions. Examples: an economy, a strategy, a knowledge base
N	Number of nodes in a system
Interdependence	The extent to which the value or payoff of one element depends on other elements
K	Number of nodes whose states affects a focal node's value, i.e. the number of nodes with which a focal node is interdependent
State of node i	$s_i = 0$ or 1
Configuration	$\mathbf{S} = \{s_1, s_2, s_3 \ldots s_N\}$
Value contributed by a node	$c_i = c_i\ (s_i;\ s_{i1}, s_{i2} \ldots s_{iK})$
Value of System	$C(\mathbf{S}) = [\Sigma_i\ c_i\ ] / N$
Landscape	Set of all possible configurations and the value associated with each configuration
J	Number of clusters
N_J	Number of nodes in a cluster = N/J
Cluster	$\{1,2 \ldots N_J\}\ \varepsilon\ \mathbf{G}_j$, j=1 to J
Cluster value	$C(\mathbf{G}_j) = [\Sigma_i\ c_i\ ] / N_J$, $i\ \varepsilon\ \mathbf{G}_j$
Coupling	Decision taken on how the search across two interdependent elements should be combined L_{ij} = the weight given to the state of node j by the decision-maker in deciding the state of node i
Integration	Coupling between clusters
Structure	**L** – set of couplings between all elements of the system
Experiential search	Trial and error search in which firms make an online evaluation of alternatives and accept those trials that

	are successful
Cognitive search	Off-line evaluation of alternatives where testing is performed on mental models of the environment

1 INTRODUCTION

> "The aim of science is not things themselves, …, but the relations among things; outside these relations there is no reality knowable"
>
> - Henri Poincare in *Science and Hypothesis* (1905)

1.1 The research questions

In this dissertation, I examine the impact of coupling that exists between the knowledge elements of a firm on the firm's technological search activity. The couplings between the elements of a firm's knowledge base comprise the structure of its knowledge base. I define coupling as the decision made on how the search across two knowledge elements should be combined and distinguish it from interdependence, which is the inherent relationship between these two elements. I ask two questions: 1) How does the structure of a firm's knowledge base impact the usefulness of a firm's inventions? 2) How does the prior structure of a firm's knowledge base affect the malleability of the knowledge base? Malleability is defined as the capacity for adaptive change.

1.2 Theoretical perspectives and motivation

The knowledge-based view of the firm suggests that the firm's knowledge base, the domain of search and the type of search are some of the key determinants of the effectiveness of technology search (see Figure 1). The domain of search represents the choice between exploitation and exploration (March, 1991). The two broad types of search considered in this study are experiential search and cognitive search (Gavetti and Levinthal, 2000). Experiential or trial and error search involves online evaluation of alternatives and acceptance of those trials that are successful. Cognitive search involves off-line evaluation of alternatives where testing is performed on mental models of the environment. Prior literature in this area has mainly conceptualized a firm's knowledge as a set of elements or components (Stuart and Podolny, 1996; Ahuja and Lampert, 2001; Fleming, 2001; Katila and Ahuja, 2002). In addition to the elements themselves, a firm's knowledge resides in the relationship or coupling between these elements as well. Considering the structure of these relationships can provide additional insight into the factors that affect technology search.

The effectiveness of technological research can be measured in two different ways. One, it can be measured as the usefulness of inventions that are being generated in the current time period. Second, it can be measured as the usefulness of inventions that are generated in later time periods. For future inventions to be generated, a firm's knowledge base has to change to keep pace with a changing technological environment and to avoid the exhaustion of useful combinations (Fleming, 2001). This capacity for adaptive change is termed here as malleability. Technology search in the current time period (a flow variable) has an important effect on the changes that occur in a knowledge base (a stock variable). Hence, it is useful to examine the effect of structure in the current time period on the changes that occur in the knowledge base. Looking at how a knowledge base (and implicitly, its structure) changes also makes it possible to address the issue of what determines structure. Hence, the two outcomes that are being studied in this dissertation are the usefulness of inventions generated in the current time period and the changes that occur in a knowledge base.

The motivation for studying the impact of structure is as follows. A technological invention can be seen as a recombination of existing knowledge elements (Gilfillan, 1935; Schumpeter, 1939; Fleming, 2001). For example, a new type of storage device that is being developed by IBM is based on punching holes using a scanning tunneling microscope which was invented in 1981 and whose initial purpose was to produce images of single atoms (Chang, 2002). Like computer punch cards, an early form of computer storage, this new system also stores information in holes, though of a much smaller size. Thus, recombining one element of knowledge, holes to store data, with another element, scanning technology, resulted in a new invention.

The large number of potential combinations of existing elements leads to a combinatorial explosion of the space of possible inventions. For instance, with just 100 elements and considering the simple case of an element being used/ not used, the number of possible combinations is 2^{100}. The actual number of knowledge elements is a much larger number. The NK-model has been developed by Kauffman (1993) to study such computationally complex problems. The two key parameters of the NK model are N, the number of elements in a system (here, technology) and K, the number of interdependencies between the elements. These two parameters can be used to generate N-dimensional landscapes that are either smooth or rugged. Useful inventions can be seen as the peaks on such a landscape. Computational complexity refers to the fact that it is difficult to locate these peaks on such N-dimensional landscapes. To know how the search process can be improved, it is necessary to study the effect of the parameters of the model and the nature (viz. domain and type) of the search process.

A simple example of the elements in a technology (design of a coffee mug[1]) is shown in Table 1. Each element can exist in various states. For example, the material of the coffee mug can be either plastic or ceramic. The interdependencies across these elements are shown in Table 2. For example, the manufacturing process depends on the type of material. The goal of technology search is to identify a set of states or a configuration that results in a coffee mug with certain desirable properties. Mug 1, a ceramic mug, and Mug 2, a plastic mug, (Table 1) represent the outcomes or the artifacts generated by this search process.

Prior literature has discussed the effect of interdependence (high vs. low) and the nature of search (local vs. distant, experiential vs. cognitive) on the effectiveness of search (Kauffman, 1993; Kauffman et al 2000; Gavetti and Levinthal, 2000). An important result derived by Kauffman (1993) is that as K (the degree of interdependence) increases, the landscape becomes more rugged, making it difficult to locate good peaks.

[1] While this example refers to the design of a product and not a knowledge base, it still provides a useful illustration of the concepts of interdependence and coupling.

This deterioration in the outcomes of the search process as the number of interdependences in the system increases is termed as the complexity catastrophe (Kauffman, 1993). I develop an extension of the NK-model by introducing the concept of coupling and seek to show that coupling has a significant impact on the effectiveness of search even on landscapes that are rugged.

The concept of coupling can be illustrated as follows[2]. In designing the coffee mug, the designer can partition the elements into subsets. A simple way would be to partition the elements into those related to manufacturing, the vessel and the handle (Table 3). The design process can be then carried on independently in these three sub-sets; this idea is captured in the concept of coupling[3]. In this particular example, the search processes for the elements in each subset are strongly coupled with each other and the search processes for elements that are in two different subsets are weakly coupled. The pattern of these couplings comprises the structure of the knowledge base of the firm.

This example also brings out the differences between interdependence and coupling (summarized in Table 4). The decision on which elements should be strongly coupled and which elements should be weakly coupled belongs to the made world – the world of human designed artifacts. In contrast, interdependence exists in the natural world – the world of laws of nature. These laws (going by our current knowledge) imply that unlike plastics, ceramics cannot be injection molded. A second important difference is that

[2] A formal definition of coupling is provided in §2.3 after the NK model is discussed in more detail.
[3] The concept of coupling is closely related to the idea of modularity, as discussed later.

interdependence is often not known a priori. For example, it may be that ceramics can indeed be injection molded but we do not how to do it as yet. Uncovering such previously unknown relationships or getting a better understanding of these relationships is a very important aspect of technology search. I develop arguments on how coupling plays an important role in uncovering or improving our knowledge of these interdependencies.

To hypothesize about the desired structure of a knowledge base, I draw upon the literature on design modularity and the related work on nearly decomposable systems (Simon, 1962). In particular, I seek to show that an intermediate level of coupling between clusters of a firm's knowledge elements achieves the right balance between exploitation and exploration that is required for effective technology search. Further, I seek to show that such a structure makes a knowledge base malleable, mainly because it increases the absorptive capacity of the firm with respect to knowledge generated through either experiential or cognitive search.

1.3 Research Design

In the first part of this dissertation, I examine the effect of coupling on the effectiveness of search on NK landscapes through a simulation-based study. These simulations extend the work done by Kauffman and his colleagues (Kauffman, 1993; Kauffman et al 1994; Levitan et al, 1999). I also use these simulations to show that the optimal level of coupling is associated with a balance between exploration and exploitation.

In the second part of the dissertation, I use the results from the simulation study to build hypotheses that are tested empirically in the context of the worldwide semiconductor industry. Longitudinal data from 1981 to 1999 was used. A number of reasons motivate the choice of semiconductors as the setting for the study. First, the high R&D intensity of the semiconductor implies that technology search is of considerable importance in this industry. Second, use of scientific knowledge is taken as a measure of cognitive search in this study. As the semiconductor industry has a high reliance on scientific knowledge (Klevoric et al, 1995), it provides an opportunity to study the effects of cognitive search.

1.4 Contributions

This dissertation makes a contribution to the literature on complex adaptive systems by introducing the concept of coupling into the NK model. Prior research, for the most part, has treated interdependence and coupling as equivalent concepts (or defined coupling as interdependence across organisms (Kauffman, 1993)). The issue of how knowledge of interdependencies is accumulated also has not been considered. This dissertation brings out the difference between the two concepts and goes further by examining the role of coupling in how interdependencies are discovered. Following Kauffman (1993), many researchers have argued that interdependencies in a system should be reduced to avoid the complexity catastrophe. I point out that changing interdependencies is beyond the control of a decision-maker, especially in the case of technology search. I argue that instead of trying to reduce interdependencies, one should focus on choosing the appropriate structure of the coupling matrix to mitigate the effects of the complexity catastrophe. Results from computer simulations show that a nearly decomposable structure improves the search on NK landscapes, as compared to a completely decomposed structure or no structure, even when interdependencies are pervasive.

Second, this study makes a contribution to the literature on modularity by making clear the mechanisms through which modularity affects technology search. It connects the literature on modularity (and the associated literature on nearly decomposable systems) with the NK model. Prior research has mostly assumed that near decomposability exists in the interdependence matrix. I argue that near decomposability actually exists in the coupling matrix and show that this near decomposability of the coupling matrix improves the search process *whether or not* the interdependence matrix is nearly decomposable. I develop on Levitan et al's (1999) idea that complete modularity achieves the right balance between exploitation and exploration and show that near decomposability (i.e. modularity combined with integration between modules) has the same effect. Further, I seek to show that near decomposability in the coupling matrix makes the knowledge base malleable by increasing the absorptive capacity of the firm with respect to the knowledge generated through experiential or cognitive search.

Third, this study contributes to our understanding about the role of science in technology search. Prior research has suggested that science provides knowledge of interdependencies (Fleming and Sorenson, 2001). However, the mechanism through which such knowledge is used has not been made clear. In this study, I seek to show that scientific knowledge about interdependencies is mainly used in changing the structure of the coupling matrix. A more generalized implication that can be drawn from this study is that the knowledge generated through experiential or cognitive search, in addition to affecting the elements, affects the structure of the knowledge base as well.

Fourth, this study is a part of a planned research stream that explores the application of Complex Adaptive Systems (CAS) theory to the fields of management and strategy. In further work, I intend to apply the concept of coupling to issues such as organization design, firm scope and intermediation. The idea of near decomposability in the coupling matrix can be applied to coupling between organizational sub-units (the issue of organization design) and coupling between firms (the issues of firm scope and intermediation). In a related paper, I am attempting to show that the concept of coupling provides an explanation of the effect of Information Technology on firm scope that improves upon the explanations provided by the traditional theories of the firm. In further work, I intend to explore the effects of IT on organization design and intermediation by using the concept of coupling.

From an empirical standpoint, this study introduces a new measure of coupling. This measure also captures the combinative aspects of a firm's technological competencies. It is also one of the few studies that test the results from the NK model in an empirical setting. From the managerial practice point of view, this study seeks to make explicit the desired structure of a knowledge base that maximizes the effectiveness of technology search.

2 LITERATURE REVIEW

In this section, I review the three streams of literature on which this study is based: technology search, modularity and the NK model. In the sub-section on technology search, I explore the key issues that have an impact on the effectiveness of technology search and discuss how they have been addressed by prior work. One such issue is modularity, which is discussed extensively in the second sub-section. Finally, I review the prior work on the NK model, discuss its usefulness in management and strategy and then focus on how it has been used to study technology search and modularity.

2.1 Technology Search

Technology search is defined as the search for useful inventions. In discussing the literature on technology search, I will also discuss the broader literature on search focusing mainly on firm-specific characteristics.

2.1.1 Technology search as problem solving

Technology search is usefully seen as a problem-solving activity (Nelson and Winter, 1982; Ahuja and Katila, 2002). The problem of technology search is to find useful inventions by searching through a space of possibilities. The space is usually called a technology landscape as the landscape metaphor is seen as appropriate for the problem of technology search. The goal of the search process is find hills or local peaks on the landscape. These local peaks represent inventions.

2.1.2 Technology search and bounded rationality

An important aspect of the search process is that it is governed by bounded rationality (March and Simon, 1958). Bounded rationality has two aspects. One, managers cannot calculate the optimal solution due to the limits on their cognitive ability. This is the aspect that has been studied extensively in the literature and has been used to explain local search. The second aspect of bounded rationality refers to the difficulty in knowing where the peaks are located on the landscape, not because managers lack the necessary skills but due to the difficulty in devising formal algorithms and generating close-ended solutions (Simon, 1996). The topography of the landscape cannot be determined and the location of the peaks cannot be calculated due to the computational complexity associated with the combinatorial explosion of the solution space[4]. Hence managers have to use heuristics to search for good local peaks on the landscape. The focus of this study is on this second aspect of bounded rationality.

In this study, I use the NK model (Kauffman, 1993) to explicitly model the computational complexity that is associated with search on a landscape. While many implications of complexity such as the presence of multiple optima, necessity of local search and the presence of path dependence are very much the same as the conclusions made by the extensive literature on search, the main difference between these two streams is in what they consider as the drivers of these phenomena. The prior search

[4] More accurately, it is widely believed but not proven that such combinatorial optimization problems cannot be solved in reasonable time (Rivkin, 2000). Providing a formal proof for this assertion is an important unsolved mathematical problem (http://www.claymath.org/millennium/P_vs_NP/).

literature focuses more on how search is constrained by organizational characteristics and cognitive limitations of humans whereas the computational complexity perspective emphasizes how search is constrained by the combinatorial explosion of the solution space. As such, the complexity perspective focuses on ways in which these constraints of complexity can be minimized.

2.1.3 The evolutionary nature of technological search

A second important aspect of search is its evolutionary nature. There are a large number of studies that have explored the evolutionary nature of technology search and developed a number of key ideas. First, technology search is characterized by path dependence (Nelson and Winter, 1982). Technology develops on a trajectory (Sahal, 1981; Dosi, 1988) through a series of small improvements. While most of the progress occurs through small changes (Mokyr, 2002), occasionally a large change occurs due to a technological discontinuity (Tushman and Anderson, 1986). A second important aspect of technological search is that it involves recombinant search (Gilfillan, 1935; Schumpeter, 1939; Fleming, 2001). Most, if not all, inventions are generated when known elements of knowledge are combined in a novel way. The idea that search is characterized by path dependence and recombination is present in the computational complexity perspective also, as discussed in §2.3.

Next, I define effectiveness of technological search and then discuss the determinants of the effectiveness of technology search (Figure 1). As inventions are recombinations of knowledge elements, the existing knowledge base of the firm is an important determinant of the effectiveness of technology search. In addition, the domain of search and the type of search are important determinants as discussed later.

2.1.4 Defining effectiveness of technological search

There are two important measures of the effectiveness of technological search. First, effectiveness can be measured in terms of the usefulness of inventions generated in the current time period. Second, effectiveness can be measured in terms of the malleability of a knowledge base. Broadly speaking, any changes that occur in the knowledge base of a firm (knowledge stock) would be a result of knowledge generation (knowledge flows). As shown in Figure 1, the knowledge flows associated with the search process and the inventions generated in the current time period affect the changes that occur in the knowledge base of the firm and in turn the inventions generated in the next time period. If the knowledge base is not malleable (i.e. if it is not capable of undergoing adaptive change), inventions that are derived from the knowledge base become less useful over time as the potential for recombination is exhausted (Fleming, 2001; Ahuja and Katila, 2002). Also, a knowledge base has to be malleable so that the firm can keep pace with a changing environment. Hence, malleability of the knowledge base is an additional important measure of the effectiveness of technological search.

2.1.5 The constituents of a knowledge-base

The two important constituents of a knowledge base are its elements and its structure. The elements of the knowledge base specify the position that a firm occupies on the technology landscape. The position of a firm is usually defined using the firm's existing patents (e.g., Jaffe, 1989), its R&D expenditures (e.g., Helfat, 1994) or by its human resources (e.g., Chang, 1996). As this study also uses inventions in the form of patents to define a firm's position, I discuss this method in greater detail. One such method starts by placing a firm's inventions in several technology categories, usually patent classes (Jaffe, 1989, Patel and Pavitt, 1997; Silverman, 1999; Ahuja, 2000). A vector then gives the position of a firm, with each element in the vector representing the fraction of the firm's inventions that fall in that category. Each element in this vector can be considered as a technological competence (Patel and Pavitt, 1997) or as a component competence (Henderson and Clark, 1990). Further, each firm's position can be additionally specified by its distance from its competitors (Stuart and Podolny, 1996; Ahuja, 2000) or a technology cluster (Jaffe, 1989).

The focus of this study is on the structure of a firm's knowledge base, which I argue is also an important constituent of a firm's knowledge base. The structure of a knowledge base refers to the pattern of relationships that exist between the elements. Structure represents the extent to which the search across pairs of elements is combined or coupled as discussed further in greater detail in §2.2 and §2.3. Structure also represents the combinative capabilities (Kogut and Zander, 1992) of the firm, as opposed to knowledge elements, which represent the component competencies. In §4, I seek to show that structure is an important determinant of the effectiveness of technological search.

2.1.6 The domain of search

The combinatorial explosion of the solution space implies that decision-makers cannot search over the entire space of possibilities. Instead, they have to focus their search on only a part of the solution space. This domain of search, i.e., where search is conducted, has important implications for the outcome of the search process. The domain of search can be usefully categorized as local vs. distant domains. Localness is defined in terms of distance from the current position on the landscape.

Local and distant search can be distinguished on the basis of elements that are combined. Local search can be measured by depth, the number of times a knowledge element has been used before (Katila and Ahuja, 2002), or the age of the knowledge elements (Sorensen and Stuart, 2000; Ahuja and Lampert, 2001). Distant search can be measured by breadth (across multiple technologies (Katila and Ahuja, 2002)) and use of technologies or knowledge elements that are new to the firm (Ahuja and Lampert, 2001).

Distance between positions can also be measured in terms of the boundaries that the search spans. The various boundaries that can be spanned either singly or in combination are those of a sub-unit within the firm, the firm, the industry and the focal technology (Rosenkopf and Nerkar, 2001). I use a similar idea and argue that a firm needs to create boundaries between clusters of its knowledge elements to achieve exploitation within the cluster. At the same time, coupling between these clusters is required to achieve exploratory search that spans boundaries. An example of across cluster and within firm exploration is IBM's development of a new storage device that was discussed in §1.2. In this case, knowledge about hole based storage devices and knowledge about scanning tunneling microscopes belong to different clusters and combining knowledge across these two clusters leads to an exploratory invention.

Search distance is important because of its impact on the effectiveness of technology search. Search in the local neighborhood of the current position or exploitation (March, 1991) is useful because it is easier for the firm to gain knowledge of the topography of the local neighborhood (March and Simon, 1958; refer to §2.3.1 for a more extensive discussion that is based on the NK model). So, by focusing on the local neighborhood, the firm is able to refine its technological competencies. The prevalence of local technology search has been established in a number of studies (for example, Helfat, 1994; Stuart and Podolny, 1996).

Search in a distant neighborhood or search that spans a boundary can be considered as exploration (Kauffman, Lobo & Macready, 2000; Rosenkopf and Nerkar, 2001). Exploration is necessary to achieve useful inventions (Ahuja and Lampert, 2001;

Rosenkopf and Nerkar, 2001), especially when the exploitative potential of the current neighborhood is exhausted (Ahuja and Katila, 2002). Since knowledge of the topography of the landscape in distant domains is less complete than the knowledge of the topography of the current neighborhood, the outcomes of distant search are more uncertain than the outcomes of local search (Fleming, 2001).

The distance of search has a further impact due to its reinforcing nature (March, 1991; Levinthal and March, 1993). Firms that exploit their current opportunities are stuck to a local peak on the landscape. These local peaks or learning traps (Levinthal and March, 1993; Ahuja and Lampert, 2001) make it difficult for the firm to explore a distant neighborhood and find another peak because climbing a different hill requires a firm to first climb down its current hill and experience performance deterioration. Given that firms are less certain about the topography of the landscape at a distance, they would be less reluctant to move from their current position. Similarly, exploration also tends to be self-reinforcing. When a firm explores, it is unlikely to reach a good peak immediately. To reach a good peak in the new neighborhood, the firm may need to search locally through exploitation. Since the discovery of new peaks through exploitation does not happen quickly, the firm tends to move on to a different neighborhood in the search for good peaks and then repeat the process without ever exploiting the new knowledge that it has acquired.

Given the self-reinforcing nature of both local and distant searches and their mutual incompatibility, March (1991) was doubtful whether firms could achieve the right balance between the two. However, Katila and Ahuja (2002) found that firms could indeed achieve this balance; they found that the interaction between the depth and breadth of search was positively related to the output of innovation search. I argue that increasing both the breadth and depth of search simultaneously increases the computational complexity associated with the search process. Hence if firms are successful in conducting exploration and exploitation simultaneously, they must be somehow reducing the effect of computational complexity. I seek to show that introducing coupling between the knowledge elements and developing a structure for the knowledge base is one such mechanism.

2.1.7 Type of search

While it is not possible to acquire knowledge of the topography of the entire landscape, it is possible to acquire reasonably accurate knowledge of some domains. Such knowledge is acquired in two broad ways. One, it can be acquired through experiential search or trial and error search. In experiential search, firms make an online evaluation of the alternatives and accept those trials that are successful (Gavetti and Levinthal, 2000). Typically, such search is backward looking and involves a narrow range of alternatives that are close to the current position on the landscape (Gavetti and Levinthal, 2000). Trial and error search is more successful in the neighborhood of the current position because the neighborhood positions are likely to be close in value to the value of the current position.

Second, knowledge about the topography of the landscape can be acquired through cognitive search[5] (Gavetti and Levinthal, 2000). In cognitive search, decision-makers make an off-line evaluation of the alternatives. Offline evaluation is possible because the testing is performed on mental models of the environment. Further, such mental models make it possible to engage in distant search because alternatives associated with poor outcomes can be easily discarded (Gavetti and Levinthal, 2000). For example, recent developments in computing technology have made it possible to test models through simulations (e.g., automobile crash simulations) at a much lower cost. Second, mental models that include cause and effect mechanisms are in effect providing a map of the landscape (Fleming and Sorenson, 2001b). Such a map makes it possible to search for peaks in distant areas by reducing the uncertainty associated with distant search (Fleming and Sorenson, 2001b).

In this study, use of scientific knowledge is assumed to represent cognitive search. It is possible that inventions that do not rely on science are based on cognitive search and inventions that rely on science are based on experiential search. Yet, it is reasonable to assume that, on average, an invention that relies on science is more likely to be based on

[5] While this clear distinction between experiential and cognitive search is unlikely to exist in practice, it is useful to treat them as two distinct types of search (Gavetti and Levinthal, 2000).

cognitive search than an invention that does not rely on science. Next, I briefly discuss the literature on the role of science in technology search.

While it seems most natural to assume that science improves the process of technology search, specifying the mechanism and empirically establishing the connection are not straightforward tasks. While discussing the role of science, it is important to note that many historical studies demonstrate that a large number of technological inventions occurred without any direct use of science (Rosenberg, 1992; Mokyr, 2002). The knowledge that is developed through technology is distinct from the knowledge that has been developed though science. Even when scientific knowledge is directly applicable to technology development, it has to be refined significantly before a useful invention is generated (Rosenberg, 1982; Vincenti, 1990).

Science can improve technology search by providing knowledge about cause-and-effect mechanisms. However, this can happen only when a simple scientific theory can be constructed. For example, as Rosenberg (1992) points out there is no simple theory of turbulence and hence domains in which turbulence exists are characterized by a significant amount of experimentation (e.g. wind tunnels, CAD and computer based simulations). Thus, science differs from other offline methods of evaluation (e.g., computer simulations) in that it based more on cause-and-effect mechanisms. Using the knowledge about cause-and-effect mechanisms, a firm can identify useful combinations (Henderson and Cockburn, 1994) or increase the number of elements that are available for recombination (Ahuja and Katila, 2002). Knowledge about cause-and-effect relationships is equivalent to the knowledge about interdependencies. In §4, I seek to show how this knowledge of interdependencies is used in changing the structure of a knowledge base.

2.1.8 Conclusions

Technology search is usefully characterized as a problem solving activity. The problem of technology search involves searching through a large design space for useful inventions. As the size of the design space is very large, technology search is associated with computational complexity. Another important characteristic of technology search is its evolutionary nature. Consequently, technology search is characterized by path dependence and recombinant search. Any model of technology search has to capture these essential features.

This study is concerned with the determinants of the effectiveness of technology search. Effectiveness can be measured in terms of the usefulness of current and future inventions. For future inventions to be generated, a firm's knowledge base has to change to keep pace with the environment and to avoid the exhaustion of useful combinations. Technology search in the current time period (a flow variable) has an important effect on the changes that occur in a knowledge base (a stock variable). Hence, malleability of a knowledge base is an additional important measure of the effectiveness of technology search. The determinants that are considered in this study are the knowledge base of the firm, the domain of search and type of search (refer to Figure 1). The domain of search represents the choice between exploitation and exploration (March, 1991). The two broad types of search considered in this study are experiential search and cognitive search (Gavetti and Levinthal, 2000).

As new technologies are very often (if not always) recombinations of existing knowledge elements, a firm's knowledge base is an obvious and important determinant of effectiveness. The two important constituents of a knowledge base are its elements and its structure. While prior research has considered the role of knowledge elements, the role of the structure of a knowledge base in technology search has not received equal attention. In this dissertation, I examine the role of structure in determining the domain of search. I also examine how structure moderates the effects of the domain of search and the type of search on the usefulness of inventions and the malleability of the knowledge base.

2.2 Modularity and Technology Search

In this sub-section, I discuss how the extent of modularity that is present in the structure of a firm's knowledge base affects technology search. The concept of modularity has a number of intellectual origins and consequently is defined in a number of ways. I adopt a broad definition of modularity that is based on Simon's (1962) notion of nearly decomposable systems.

2.2.1 Nearly decomposable systems

The matrix in Figure 2 represents a hypothetical nearly decomposable system in which an X in a cell implies that the row element of the cell interacts with the column element of the cell. For example, A3 and B1 interact with each other. The matrix is nearly decomposable in that one can identify three groups or modules A, B and C. All elements or components within the group interact with each other and the number of interactions that cut across group boundaries is small. It should be noted that this interaction matrix, also called as an adjacency matrix (Ghemawat and Levinthal, 2000) or an influence matrix (Rivkin and Siggelkow, 2003), indicates only whether a component interacts or not with another component and does not provide the strength of the interaction.

Decomposing a system can be seen to be the same as modularization of a system. Decomposition is usually not complete as it is neither possible nor beneficial to remove all the interdependencies that exist across modules. Hence, it is more useful to consider a continuum between modularity and integration (Schilling, 2000). High integration between the modules implies that it is difficult to identify the modules. Complete integration refers to the case where modules do not exist.

A nearly decomposable system also exhibits a hierarchic structure. Simon (1962) argues that a hierarchic structure allows for intermediate stable forms and greatly aids the process of evolution. Almost all complex systems including physical, biological and social systems seem to exhibit the property of near decomposability. This leads Simon to propose the "empty world hypothesis" – most things are only weakly connected with most other things. Further, he argues that if there were systems that are not decomposable then they would elude our understanding because "analysis of their behavior would involve such detailed knowledge and calculation of the interactions of their elementary particles that it would be beyond our capacities of memory or computation" (Simon, 1962: 477). However, he also says, "I shall not try to settle which is chicken and which is egg; whether we are able to understand the world because it is hierarchic, or whether it appears hierarchic because those aspects of it which are not elude our understanding and observation. I have already given reasons for supposing that the former is at least half the truth-that evolving complexity would tend to be hierarchic-but it may not be the whole truth" (Simon, 1962: 478).

So, while Simon (1962) believes that interdependence in the natural world is likely to be nearly decomposable, he also seems to accept that near decomposability is something that we impose on the world. Further, he does not distinguish between near decomposability of the natural world and near decomposability of the made world.

In this dissertation, while being agnostic about whether the natural world is nearly decomposable or not, I argue (in §3 and §4) that near decomposability exists in the made world. It is important to note that the concept of near decomposability is applicable to coupling as well and not just the underlying interdependence structure (see

Figure 3). Near decomposability in the coupling matrix results in modular clusters (that have high coupling within themselves) and integration (or low coupling) across these clusters. I seek to show that near decomposability or the hierarchic nature of the made world helps us in understanding the natural world. This understanding can in turn be used to design newer artifacts of the made world.

2.2.2 Implications of near decomposability

What are the implications if the systems that we seek to analyze are nearly decomposable? One important goal would be to try to guess the appropriate decomposition of the system as modularization that matches the underlying decomposition does better than both mismatched modularization (Ethiraj and Levinthal, 2003) and no modularization. A second goal would be to identify all the interdependencies that exist across modules after a system has been modularized and incorporate them into design rules (Baldwin and Clark, 2000). These design rules would ensure that any changes made at the module level remain consistent with the changes made in the other modules.

In addition to the above two ways in which modularity makes use of the underlying decomposable structure, there are other benefits that modularity provides. These benefits can be categorized as those that pertain to the search process and those that pertain to the outcome of the search process, i.e., the end product (Baldwin and Clark, 2000; Sanchez and Mahoney, 1996). The benefits of modularity in the end product such as economies of substitution (Garud and Kumaraswamy, 1995), ease of manufacture[6], meeting diverse customer preferences and ease of repair[7] are not directly applicable to technology search because a technology search that is not modular can still generate products that are modular.

The benefits of modularity in search exist because modularization obtains the benefits of breaking a large problem into manageable small problems that have fewer constraints. Integrating the solutions of these smaller problems can remarkably improve the solution of the larger problem. (The simulation study presented in §3 discusses why this remarkable improvement occurs). Further, modularization leads to specialization (for instance, Adam Smith's famous example of specialization in pin-making) and enables the development of component specific knowledge. Such component specific knowledge can be usefully recombined in developing new technologies (Baldwin and Clark, 2000; Schilling, 2000). When modularization does not exist, that is when components do not exist, the firm will find it difficult to reuse parts of its earlier technology[8].

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[6] Modularity simplifies manufacturing and lowers manufacturing costs.

[7] Modularity makes it easier to repair because in a modular product, only the defective part needs to be replaced. Further, replacing the defective part can be done on site, which further reduces the cost of repair and maintenance.

[8] For example, Computer Numerical Controlled (CNC) machines have both hardware and software compared to non-CNC machines that have only hardware. Firms which manufacture CNC machines can reuse software related knowledge while this opportunity does not exist for firms that manufacture non-CNC machines.

The benefits of modularity have also been addressed by the literature on loose coupling in organizations (Weick, 1976; Orton and Weick, 1990). The definition of loose coupling provided by Weick (1976) is (deliberately) under specified. Consequently, it has been used in addressing a variety of conceptual issues, summarized in Orton and Weick (1990). The use of the concept of coupling in this study is limited to what Orton and Weick (1990) term as the voice of organizational outcomes of loose coupling[9].

2.2.3 Modularity and the literature on loose coupling

The organizational outcomes of loose coupling discussed in the literature summarized by Orton and Weick (1990) include persistence, adaptability, buffering and satisfaction. While persistence refers to stability and resistance to change, adaptability refers to accommodation of the change. Orton and Weick (1990) make no attempt to reconcile these divergent views. I suggest that distinguishing between coupling and interdependence makes it clear how such divergent outcomes can be observed. When interdependence between sub-units is low or does not exist, then changes in one module do not affect the components of other modules and this leads to persistence. When interdependence exists between modules but coupling between modules is low, experimentation is possible at the module level because low coupling implies independent decision-making across the modules. Interdependence between modules implies that changes that occur within a module affect other modules and induce

[9] The other themes that Orton and Weick (1990) explore are causes of loose coupling, types of loose coupling, direct effects of loose coupling and compensations for loose coupling.

changes in other modules. Thus, even when low coupling exists, changes in a module can lead to system wide adaptation.

Buffering (Thompson, 1967) or sealing off one module from another is seen as a useful outcome of modularization because such sealing off is thought to be necessary to prevent the spread of problems (Weick, 1976). For example, in software design, modularity has been seen as very desirable because it reduces ripple effects. Large ripples occur when a change in one module requires a long sequence of changes in other modules. Similarly, modularization has been extolled in the product design literature due to its ability to limit ripple effects (Baldwin and Clark, 2000). However, ripple effects actually increase when modularization is attempted in a system that has a large number of interdependencies between the modules (Baldwin and Clark, 2000). Further, choosing independent modules and avoiding ripple effects is not actually desirable in technology search. In §4, I argue that such ripple effects can be equated with exploration and hence should not be prevented from occurring.

Finally, loose coupling increases satisfaction because independence in decision-making leads to self-determination and efficacy (Weick, 1976). The smaller size of groups increases task visibility and deepens social interactions (Orton and Weick, 1990). Such effects are important in the case of technology research as well because the presence of social interactions improves the communication process among research personnel (Allen, 1977). Further, independence in decision-making also makes it possible to set performance objectives, provide incentives and improve monitoring (Orton and Weick, 1990).

2.2.4 Modularity in different contexts

While modularity has usually been discussed in the context of product design, recent work has extended the idea to other contexts such as organization design (Sanchez and Mahoney, 1996), firm scope (Brusoni et al, 2001) and technology search[10] (Fleming and Sorenson, 2001a). Two important issues need to be considered when one extends the concept of modularity across contexts.

First, are the principles of modularity likely to remain the same as one moves from the context of product design to other contexts? Specifically, are there any aspects of modularity as applied to technology search that differ from modularity in other contexts? While most principles of modular design seem to be applicable across contexts, one has to keep in mind a few differences. As discussed above, modularity in product design can have an effect on design development, product manufacture and assembly and product use including maintenance and repair. In technology search, only the development stage may exist. Given the multiple needs for modularity, there may be a greater need for full modularity (i.e. less integration) in product design. In contrast, it may be possible to accommodate more integration between knowledge clusters in the case of technology search.

[10] Modularity in product design and modularity in technology search are different in that the latter refers to modularity in the knowledge base of the firm.

Second, what is the effect of modularity in one context on modularity in another context? It turns out that decisions made regarding the extent of modularity and partitioning in one context can affect the extent of modularity and partitioning in another context. For example, modularity in product design is reflected in modularity in organization design and firm scope (Henderson and Clark, 1990). Baldwin and Clark (2000) show how product modularity in the computer industry (e.g., modular design of IBM's system/360) led to the creation of new firms and eventually to the formation of industry clusters. At the same time, modularity in organization design and firm scope can also affect product design and technology search. The effects of divisionalization (Argyres, 1996; West, 2000) and geographical localness in spillovers (Jaffe et al, 1993; Almeida and Kogut, 1999) on technology search provide evidence that modularity in other contexts can affect technology search.

This correspondence between modularity in different contexts raises an important question: Is modularity in the knowledge base of a firm just an outcome of modularity in product design? While modularity in product design may be related to modularity in the knowledge base, the partitioning in the two contexts may not match exactly (Brusoni et al. 2001). Further, firms tend to have higher technological diversification than product diversification (Patel and Pavitt, 1997). More importantly, a given knowledge element can be used across a number of products and evidence exists that firms diversify to make use of their existing technological resources (Silverman, 1999).

Hence, it does not seem likely that modularity in the knowledge base of a firm is just a consequence of modularity in product design.

2.2.5 Structure and malleability of a knowledge base

One important outcome of the correspondence between modularity in the knowledge base and modularity in organization structure is that it increases the rigidity of the structure of a firm's knowledge base, as discussed next. Presence of modularity in an invention implies that further changes in the invention can occur at two levels: at the level of the module and at the level of the architecture, i.e. the relationships between the modules. Henderson and Clark (1990) suggest that these two types of innovations have different consequences for firms. After a dominant design emerges firms become more adept at module innovation. However, when architectural innovations are required, firms may not be successful in making the necessary changes in the product architecture. The existing organization structure and accompanying information channels become rigid making it difficult for the firm to recognize that change is required in the architecture or make the required changes when the problem is recognized.

A similar problem can be observed when the above logic is extended to the structure of a knowledge base. The correspondence that exists between the structure of the knowledge base and the structure of the organization may make the knowledge base rigid. In this study, I argue that structures differ in their capacity to facilitate change. As

I later discuss in §4, the ability to adapt may depend on the level of coupling between the clusters.

2.2.6 Conclusion

In this dissertation, I borrow from the literature on modularity and the associated literature on nearly decomposable systems to study the effect of the structure of a knowledge base on technology search. Structure represents the pattern of interdependencies that exist between knowledge elements. The literature on modularity and the literature on loose coupling suggest that a pattern that exhibits the property of near decomposability has certain desirable properties such as potential for recombination, persistence and adaptability. Near decomposability implies the existence of clusters that have a large number of interactions within themselves along with weak interactions across clusters.

While previous literature has suggested that near decomposability exists in the underlying interdependencies (for example, Simon, 1962; Ethiraj and Levinthal, 2003), I argue that near decomposability can be usefully applied to coupling as well. In §3, I show that near decomposability in the coupling matrix improves the search process even when the underlying interdependencies are pervasive. This distinction between coupling and interdependence can also be used to explain some of the divergent outcomes of loose coupling such as persistence and adaptability.

Lastly, it is important to study the inertial properties of a structure, as inertia in structure will lead to rigidity of the knowledge base. In §4, I argue structures differ in their ability to facilitate change. Specifically, I hypothesize that a nearly decomposable structure has the additional attractive property that it can facilitate change.

2.3 The NK model

As §2.1 makes it clear, the features of the landscape and the nature of the search process affect the outcomes of the search on a landscape. As such, it would be useful to understand the factors that affect the features of the landscape. A formal model that can capture the essential features of the landscape would be very helpful in furthering our understanding of the search process.

The formal model that is presented in this study is based on the NK model proposed by Kauffman (1993, 1995). The NK model was developed in the context of evolutionary biology to explain the emergence of order in living systems. Even though the model had been developed in evolutionary biology, it has proved to be useful in management and strategy, albeit with some modifications. I will first discuss the basic features of the NK model, its usefulness and limitations when applied in management and strategy (especially to the problem of technology search), and then discuss what has been suggested in prior work to overcome these limitations. As the subsequent discussion shows, incorporating decision-making, knowledge and modularity into the basic NK model enhances the applicability of the NK model to the organizational domain.

2.3.1 A brief introduction to the NK model

The NK model defines a system in terms of two key parameters: N, the number of elements or nodes and K, the number of interdependencies for each node. Definitions of the important concepts used in the basic NK model and the extended model are provided in the Glossary. The ability of this model to generate a wide variety of interesting landscapes with just two parameters is an important reason why this model has been popular. The search problem is defined in terms of finding the configuration of the system that has the highest fitness or value (see Table 5 for an illustration). The states of the various nodes in the system constitute the configuration of the system. So, a configuration **S** is a vector $\{s_1, s_2, s_3 \ldots s_N\}$ where s_i, the state of the node i is an integer. It is assumed that the state of the node can be either 0 or 1 as restricting the possible states to these two integers simplifies the model without any loss in generality (Kauffman, 1993). Each configuration has an associated value or payoff that is an average over the values contributed by each node. The value that each node provides to the entire system depends on its own state and the states of K other nodes. The notion that any node is interdependent on K other nodes is captured through the effect that the states of the K nodes have on the focal node. So, the contribution of each node is $c_i = c_i (s_i; s_{i1}, s_{i2} \ldots s_{ik})$ and the value of the system $C(\mathbf{S})$ for a configuration **S** is given as

$C(\mathbf{S}) = [\Sigma_i\, c_i] / N$

The various configurations can be represented as vertices of a N-dimensional hypercube (Kauffman, 1995). (See Table 5 for an illustration). Each vertex is connected to N other vertices, with each vertex being different from the focal vertex in the state of just one node. These N dimensions along with the additional dimension of value associated with each vertex constitute a landscape[11]. Searching for good configurations is equivalent to searching for peaks on the landscape. I will next discuss the features of the NK landscapes that have an effect on the search outcomes when search is conducted through a simple hill-climbing procedure.

First, Rivkin (2000) shows that the problem of finding the configuration with the highest value is computationally intractable for K >2. As the problem is NP-complete (Kauffman, 1993; Rivkin, 2000), any general search procedure is likely to have non-deterministic polynomial time solutions[12]. For example, if all possible configurations are enumerated, when N =10,000 (a number much smaller than the number of technological elements) the possible number of configurations of the system that have to be evaluated is $2^{10,000}$ (~ $10^{3,000}$ whereas the number of known particles in the universe is less than 10^{100}). Kauffman (1995) concludes "...there is not enough time since the Big Bang to find the global optimum" when the number of configurations is so large. Such a combinatorial explosion occurs even for much smaller values of N (Rivkin, 2000).

[11] In simulations, the value of each configuration is randomly assigned a value between 0 and 1. Kauffman (1993) finds similar results in his simulations for other distributions of values.
[12] In other words, the solution time increases as an exponential function of N.

The combinatorial explosion of the solution space and the resultant computational complexity require the use of heuristics and abandoning of the quest for the globally optimal solution. It is not possible to possess knowledge about the topography of the entire solution space. Competition, evolution or any foreseeable growth in computing power is unlikely to alter the necessity of using heuristics. As discussed in §2.1.2, this computational complexity results in bounded rationality of managers (Simon, 1992). Computational complexity implies that the effect of the features of this model on search outcomes have to be studied through computer simulations. The following discussion is based on the simulation results presented in Kauffman (1993, Chapter 3).

Second, the NK landscapes have multiple optima[13]. Further, the number and mean values of local optima are related to the two parameters of the model (Kauffman, 1993) in interesting ways. When K=0, changing the state of a node has no effect on the contribution of the other nodes. A change in the state of a node has a small effect on the system value. So, neighboring points[14] on the landscape are close to each other in value making the landscape smooth (i.e. high spatial autocorrelation). Further, there is a single peak that can be identified quickly through simple hill climbing[15].

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[13] Whether a particular point on a landscape is an optimum or not depends on the number of mutations considered at one time. For example, a point that is a local optimum for one-mutant moves may not be an optimum for two-mutant moves. In this study, unless otherwise mentioned, a peak is a local optimum with respect to one-mutant moves.

[14] Neighboring points differ in the state of just one node.

[15] Since the contribution of one node does not interfere with the contribution of another node, it is possible to set all nodes to states where they make their highest contribution.

When K>0, any change in the state of a node affects the contribution of this node and K other nodes as well. A change in the state of a single node can thus have a large effect on the system value. So, there maybe a large difference in the value of neighboring points. Consequently, as K increases, the ruggedness of the landscape increases (i.e. less spatial autocorrelation). Further, the number of optima increases rapidly as K increases (Kauffman, 1993; Gavetti and Levinthal, 2000; Rivkin, 2000). At the extreme case of K=N-1, the landscape is fully random (i.e. no spatial autocorrelation) and even a change in the state of just one node can have a large impact on the mean value of the system. As it becomes increasingly difficult to find a configuration in which nodes are simultaneously in their optimal states, the average height of peaks found through simple hill climbing drops.

Third, a very important result obtained by Kauffman (1993) is that the average height of the peaks is highest for small values of K relative to N. The average value increases initially and then drops off rapidly as K increases from 0 to N-1. The decline in average height of the peaks as K (the measure of complexity) increases beyond its optimal value is called the complexity catastrophe (Kauffman, 1993). Kauffman (1993) suggests that the number of interdependencies has to be kept low to prevent the complexity catastrophe from occurring.

Fourth, search on the NK landscapes can also be defined in relative terms. On the NK landscape, movement from one position to another would be a movement from one configuration to another. A movement from one configuration to another would imply a change in the state of a certain number of nodes, say D. (D=1 for neighboring positions on the landscape). D, which is also the distance between the two configurations, is the number of nodes at which the two configurations have different states. Obviously, D can vary from 1 to N. The local neighborhood of the current configuration consists of all configurations for which D is small. Similarly, a neighborhood is distant when D is large.

As with search on any type of landscape, it is useful to distinguish between exploitation, which is search in the local neighborhood of the current configuration and exploration, which is search in a distant neighborhood. Search in a local neighborhood can be accomplished through local moves. A local move would be one in which only a few states are changed. A move that changes the state of just one node is called a one-mutant move. D can also be seen as the number of one-mutant moves that are required to transform one configuration to another. For example, in the illustration shown in Table 5, three one-mutant moves are required to move from 000 to 111.

Search in a distant neighborhood can be accomplished in two distinct ways. One, a series of one-mutant moves can accomplish this transformation. For example, if we look at the economy as a whole, any large-scale change that has occurred is the cumulative outcome of a number of smaller changes. As Rosenberg (1982) points out, at any given period, innovations enter the economy through a small door but have a pervasive influence. The location of these doors changes over the course of time – from machine tool and steam power in the nineteenth century to biotechnology and the Internet in recent times. Further, path dependence exists only when search is conducted through local moves. The presence of path dependence in technology search (Sahal, 1981; Dosi, 1988) and evidence that large technological changes often occur as a result of cumulative and minor technological changes (Rosenberg, 1982; Mokyr, 2002) and not just through discontinuous change (Tushman and Anderson, 1986) indicates that distant search can be accomplished through local moves as well.

However, when a basic hill-climbing strategy is used[16], one-mutant moves are unlikely to take the system away from its local neighborhood as one-mutant moves will take the system to a nearby local peak. By definition, all neighboring positions of a local peak are inferior in value. There are no further one-mutant moves that increase the value of the system and the system gets trapped at the peak. So, to accomplish distant search though one-mutant moves the basic hill-climbing search has to be modified. One such modification is to incorporate modularity, as discussed later.

A second way in which search in a distant neighborhood (at a distance, D) can be conducted is by changing all the D states at once[17]. Such a move can be termed as a long jump (Kauffman, 1993; Levinthal, 1997) or a distant move. In this case path

[16] In such a strategy, only those moves that increase the value of the system as a whole are accepted.
[17] Strictly speaking, one can think of one-mutant moves, two-mutant moves and so on till D-mutant moves. The extreme values of 1 and D are discussed here to bring out the difference local and distant moves.

dependence does not exist, as the movement of the system is not restricted to neighboring configurations. So, exploration is possible through both local moves and distant moves. I will discuss shortly the issue of when exploration should be conducted through local moves and when it should be conducted through distant moves. The choice between exploitation and exploration depends on where the peaks are located on the landscape as discussed next.

Fifth, simulation results show that the distance between the peaks increases as K increases (Kauffman, 1993). At low values of K, peaks are located close to one another. This also implies that configurations that are close to a configuration that has a low value are also likely to have a low value. So, when the system is at a configuration that has a low initial value, distant search is likely to be more useful than local search (Kauffman et al, 2000). After a peak has been found, local search is sufficient to find other good peaks as the peaks are clustered together. So, on landscapes that have low K, local search or exploitation is fruitful once a good peak has been identified.

As K increases, the peaks disperse (Kauffman, 1993; Ghemawat and Levinthal, 2000). Knowing the location of one peak does not provide much information on the location of other peaks on a rugged landscape. This has two implications. One, local search is not sufficient to find other good peaks on landscapes that have K above a certain level. Two, while distant search can lead the system to other parts of the landscape, changing the states of a large number of nodes (i.e. a long jump) moves the system to a neighborhood that has peaks with unknown values and which on average will be low on a high K landscape. As discussed later, modularity and knowledge of the landscape can improve the exploratory search process on high K landscapes.

Sixth, NK landscapes show the effects of imprinting (Levinthal, 1997). For each peak on the landscape, one can visualize a basin of attraction (Kauffman, 1993). That is, any series of one-mutant moves from a starting configuration in this basin will end up on the same peak. The sizes of the basins of attraction decrease as K increases. With large basins of attraction, configurations with large differences in their states can end up at the same peak. So, the starting configuration at which an adaptive walk begins has little effect when K is small. In contrast, when K is large and basin sizes are small, the eventual peak that is reached depends on the starting configuration. In the context of organizational level changes, this gives rise to imprinting effects whereby the organization's form at founding has a persistent effect on its future form (Stinchcombe, 1965; Levinthal, 1997).

This above description shows that the NK model generates a landscape that very much resembles a landscape discussed in the conventional search literature. Next, I will discuss prior studies that have applied the NK model in the management field and discuss the key changes to be made to the basic NK model to make it applicable to such contexts. The NK model has been used to in many different contexts as summarized in Table 6. The system can represent an organization (Levinthal, 1997), a strategy (Rivkin, 2000; 2001), a technology landscape (Kauffman et al, 2000; Fleming and Sorenson, 2001a; 2001b) and an economy (Levitan et al, 1999). The features of the NK landscapes lead to interesting results in all these contexts, which shows that the NK model exhibits certain fundamental properties.

2.3.2 Incorporating decision-making and knowledge into the NK model

As the NK model has been developed in the context of evolutionary biology, decision-making and knowledge play no role in the search process. Random mutations and adaptation (i.e. accepting a change in a configuration when it increases the fitness) can lead an organism to a peak. A random or blind search is also applicable to the organizational world when managers are limited to trial-and-error approaches. The incremental improvements that occur as a firm searches adaptively on the landscape can also be considered as learning by doing (Auerswald et al, 2000). The learning curves generated through adaptive walks on an NK landscape are very similar to actual learning curves (Auerswald et al, 2000).

Humans do make decisions in the search process and often use their knowledge in these decisions. Hence in the context of the organizational world it is important to incorporate decision-making and knowledge into the search process that is used on NK landscapes. Prior work has attempted this in many different ways. Broadly speaking, decision-making is involved in choices related to (i) the length of the move (one-mutant moves vs. long jumps), (ii) local vs. distant search and (iii) the grouping of nodes. Each of these decisions is affected by the knowledge that the decision maker possesses.

Knowledge associated with the landscape can be classified into knowledge about nodes and knowledge about the interdependencies between the various nodes. Two key issues arise with respect to such knowledge: 1) How is knowledge about nodes and interdependencies used to improve the search process? 2) How is such knowledge obtained?

The knowledge about nodes would be in terms of knowing the sets of states (i.e. configurations or points on the landscape) that are associated with high values (Rivkin, 2000). The knowledge about useful configurations can be obtained by a simple trial and error search. Even without having any knowledge of the interdependencies on the landscape, the decision-maker can make a change in the state of a randomly selected node. Such trials are accepted when the value of the system increases. A sequence of such trials or an adaptive walk takes the firm to a local peak. Local search can then identify other nearby peaks. The decision-maker can use such knowledge in replication whereby the firm can set various components (of a strategy or an organizational form) to the same states that have proven to be useful (Rivkin, 2000). Given the knowledge of the required states, it is not difficult to make long jumps on the landscape and change the states of a large number of nodes simultaneously. However, knowledge of the required states would provide only a limited value to a firm because replication and local search will eventually be limited by the exhaustion of technology potential (Fleming, 2001).

While it seems that knowledge of interdependencies is more useful, showing how knowledge of interdependencies helps the search process is not a straightforward task. Fleming and Sorenson (2001b) argue that scientific knowledge acts as a map for technology search. Science provides inventors knowledge about the interdependencies that exist between various components and thus can be used in the search for peaks on the landscape. However, they do not discuss how knowledge of interdependencies helps in the search process. It is important to show such knowledge results in a search process that does better than trial and error search because even with trial and error search that is not based on any knowledge of interdependencies (as is the case in the original NK model), reasonably good peaks can be attained.

Gavetti and Levinthal (2000) suggest that knowledge of interdependencies can be used to create cognitive maps or mental models of the interdependencies between the various components of the system. One can then search for good configurations on these cognitive maps. Gavetti and Levinthal point out that such cognitive maps would necessarily be caricatures of the actual landscape and hence contain fewer dimensions than the actual landscape. So, the outcome of cognitive search would be a set of states for a subset of nodes (N1) that is optimal for this subset. The decision-maker can freeze the states of these nodes and then search locally for the remaining N-N1 nodes.

(Freezing the states of the N1 nodes leads to a better peak than subsequent local search that includes these N1 nodes). Gavetti and Levinthal found in their simulations that such prior search on cognitive maps increases the average heights of the peaks that are subsequently attained.

Interestingly, the initial search on the cognitive map leads to only a modest gain in value and most of the performance enhancement that arises is due to the subsequent local search (Gavetti and Levinthal, 2000). The initial search on the cognitive map helps because it places the system in an attractive basin (i.e. a basin in which the peak is high). This result is consistent with the evidence on the delayed effect of science (an example of cognitive search) on technology search. Use of science rarely provides an immediate benefit. A substantial effort is required before an invention that is based on scientific knowledge becomes useful (Vincenti, 1990).

How is such knowledge of interdependencies obtained? As discussed before, science plays an important role in identifying these interactions[18]. Further, knowledge about states and interdependencies can also be obtained by observing competitors who have attained such knowledge (Rivkin, 2000; Rivkin, 2001). Naturally, it is difficult to observe the states that are attained by competitors and such knowledge can be copied only imperfectly. Even the firm that has attained the valuable configuration has imperfect knowledge of the states, though its knowledge is likely to be superior to its

[18] This in turn begs the question of how scientists uncover the underlying interaction structure.

competitors' knowledge. Such imitation by competitors becomes difficult as the number of interdependencies increases (Rivkin, 2000). As such, firms that seek to prevent imitation should increase the number of interdependencies among the components of their strategies. However, as the number of interdependencies increases, replication also becomes increasingly difficult (Rivkin, 2001). Rivkin demonstrates that when a strategy has moderate interactions, the gap between a firm's ability to replicate the strategy and a competitor's ability to imitate the strategy is at its highest.

In addition to cognitive search, are there other ways in which knowledge of interdependencies can be used in the search process? In addition to the use of scientific knowledge and imitation, are there any other mechanisms for identifying interactions? In the next section, I argue that coupling plays a key role in using the knowledge of interdependencies as well as in uncovering the underlying interdependence structure.

2.3.3 NK model and modularity

From the above simulation results, one can derive the broad implication that a complex system that has a low density of interdependencies between the constituent parts is ideal for search, especially when search is conducted by biological agents (Kauffman, 1993: 67). Levinthal and Warglien (1999) extend this logic to the organizational domain and recommend that interdependencies should be tuned based on the outcome that is desired. They suggest that interdependencies should be reduced to achieve robust designs and interdependence should be increased to achieve higher levels of exploration. I depart from this logic and argue that it is more appropriate to define interdependence as something that is given and cannot be changed (as Levinthal and Warglien (1999: 343) themselves note). Also, interdependence is not known a priori and uncovering interdependencies or relationships that exist in the natural world is a key goal of the search process. Further, it is quite possible that the number of interdependencies in a given system is high. In such a case, one has to resort to other mechanisms to avoid the complexity catastrophe and as discussed next, modularity is one such important mechanism.

To show how modularity can be incorporated into the NK model, it is first useful to define coupling. Most prior work has not distinguished between interdependence and coupling. (For an exception, see Fleming and Sorenson (2001a) who point out the difference but do not further pursue the issue). For example, Levinthal (1997) equates an organization with low interdependencies among the constituent elements to a loosely coupled organization. The term coupling also has a different meaning in earlier work on the NK models (Kauffman, 1993; Levinthal and Warglien, 1999). Kauffman defines coupling, C, as the number of interdependencies that exist across organisms as opposed to K, the number of interdependencies within an organism. In this study, I propose to use the term coupling as it is normally used in the management field. Next, I define coupling, show how it is different from interdependence and discuss prior work on modularity and the NK model.

In the basic hill-climbing heuristic used in the NK model, any change in the state of a node is accepted only if it increases the value of the system as a whole. One can think of other search procedures in which the criterion for accepting a move is based on value of a node or a group of nodes rather than that of the entire system. Coupling (L) is defined here as the weight attached to the value contributed by another node in deciding the state of the focal node[19]. The search for higher value at a given node is based on changes in C'_i, which is defined as $C'_i = L_{ii}*C_i + \Sigma L_{ij}*C_j$, j=1 to N and ≠ i. In this study, I set L_{ii} =1 and restrict the value of L_{ij} to the range (0,1) and leave the study of $L_{ij}>L_{ii}$ to further research[20].

Zero coupling between two nodes implies that the search processes across the two nodes are conducted independently. A change in the state of a node is accepted when it results in an increase in the contribution of the node even if it reduces the value of the other node. Perfect coupling (i.e. L_{ij}=1) between two nodes implies that there is a single and common search across the two nodes. When L_{ij}=1 for all pairs of nodes, the contribution of the rest of the system is given the same weight as the contribution of the focal node. So when L_{ij}=1 for all pairs of nodes, the search process is exactly equivalent

[19] Rivkin and Siggelkow (2001) also define a similar search criterion, but use it to model incentives. Instead of L, they define a parameter INCENT. When INCENT = 0, a manager in charge of a group considers the value from only his group. When INCENT =1, a manager gives equal weight to the rest of the system as well.
[20] When $L_{ij}>L_{ii}$, the contribution of the rest of the system is given higher importance. The economic and organizational implications of $L_{ij}>L_{ii}$, if any, are beyond the scope of this study.

to a system level search. Only those moves that result in an increase in system level value are accepted. Implicitly, L_{ij}=1 for all pairs of nodes in the original NK model.

The difference between interdependence and coupling (summarized in Table 4) is as follows: interdependence is the extent to which the value contributed by a node is affected by the states of K other nodes where as, coupling is the extent to which the decision-maker *considers* the contributions of another node in deciding the state of the focal node. While interdependence is what exists in the natural world and is governed by natural laws, coupling is a choice made by the decision-maker (Fleming and Sorenson, 2001a) in the made world or the "artificial" world (Simon, 1996). Earlier research has suggested that decision-makers should focus on low K landscapes when they want to identify peaks easily. Unfortunately, this may not be possible as changing interdependence may be beyond the scope of decision-makers. In any situation where it seems that decision-makers are changing the level of interdependence, it is easy to show what is actually being changed is the level of coupling.

Specifying coupling between a pair of nodes serves a very important purpose of specifying group or module membership. For example, a nearly decomposable coupling matrix divides the system into groups or modules (see Figure 3b) even when interdependence is pervasive (as implied by the number of Xs in the interaction matrix (Figure 3a)). All nodes that have a coupling of 1 between each other (or more generally, a coupling that is high) can be identified as a group. A level of coupling that is greater than zero between two groups indicates that there is some integration across the two groups. So, integration between the groups defines the continuum between complete modularity (i.e. no across group interdependencies exist) and complete integration (i.e. no groups exist). Therefore, studying the effect of coupling subsumes studying the effect of modularity and integration.

Prior work on the NK model has only implicitly addressed the issue of coupling between groups. Kauffman and his colleagues (Kauffman et al, 1994; Levitan et al, 1999) studied the effect of splitting a system into a number of groups, each with size equal to N_J, on the search process on NK landscapes (Figure 4). Kauffman et al (1994) found that a system with an intermediate group size ($1<N_J<N$) does better than a system in which there is only group ($N_J = N$) and a system in which each node is a group by itself ($N_J = 1$). This simple study demonstrates the enormous power of modularity. Their study is implicitly limited to studying the effect of zero coupling between groups. In the next section, I explore the consequences of increasing the coupling between groups and show that such coupling can increase the mean values of peaks attained even when interdependence is high. In §4, I explore the role of coupling in uncovering interdependencies and in making a knowledge base malleable.

2.3.4 NK Model and technological search

We saw that the landscapes generated by the NK Model have properties such as bounded rationality, multiple optima, local search and imprinting that are supposedly associated with technological landscapes as well. In this section, I specifically discuss the prior work that has used the NK model to study technological landscapes.

Kauffman and colleagues (Auerswald et al, 2000; Kauffman et al, 2000) have studied technological landscapes in an abstract setting. In their formal models, a configuration represents a technology recipe (Auerswald et al, 2000). Each node represents an element of the recipe. From a starting configuration, a firm randomly chooses a mutation and then walks adaptively to a peak. The peak represents a technology recipe that has higher values than other recipes. This approach has been applied to study learning by doing (Auerswald et al 2000) and optimal search (local vs. distant search) distance (Kauffman et al, 2000). This approach does not address the issues of either recombination or modularity.

Fleming and Sorenson (2001a) applied the NK model to the problem of technology search in an empirical context. Since this study builds on their work, it is discussed in detail here. In their model, N is the number of components (viz. the number of patent sub-classes to which each patent belongs) that are combined in an invention (viz., a patent) and K is the interdependence among these components. It should be noted that the analysis is at the level of a patent in their study. Fleming and Sorenson (2001a) study the effect of interdependence between the components, the number of components and the interaction between interdependence and the number of components on the usefulness of the resulting innovations. Usefulness is measured as the number of citations that a patent receives. A key result obtained by Fleming and Sorenson (2001a) is that intermediate values of K are associated with high usefulness, which is in agreement with the basic NK model.

A few important issues should be noted about the above formulation of the problem. First, it is implicit that coupling is the same across all pairs of the components. That is, a system-level search is conducted across all the components whereby a configuration that is optimal is found. This particular formulation does not accommodate intermediate values of coupling. Second, the authors are silent on whether the inventors make a local search or distant search. Third, it is unclear whether their measure of K actually represents interdependence. They measure K as the inverse of the ease of recombination of a subclass and then average across all the subclasses that are present in the invention. According to this measure, a patent that has subclasses that have been combined with a wide variety of other subclasses has low interdependence and a patent that has subclasses that have been combined with only a few other subclasses has high interdependence. Ease of recombination may thus reflect the potential for recombination and may not reflect interdependence at all.

2.3.5 Conclusion

The NK model is a formal approach to studying the process of search on landscapes when the search problem is computationally complex. The NK model is appropriate for addressing issues such as path dependence, recombinations, domain of search and type of search, which are all key issues in technology search. However, the model (which has its origins in evolutionary biology) has to be modified before it can be applied in the fields of management and strategy. Specifically, decision-making and knowledge have to be incorporated into the model to account for two of the major differences between organisms and organizations.

Prior research in the management literature has incorporated knowledge of useful configurations (Rivkin, 2000; Rivkin, 2001) and knowledge of interdependencies (Gavetti and Levinthal, 2000) into the NK model. An additional type of knowledge that needs to be incorporated into the NK model is the knowledge of which nodes should be grouped or coupled together. While earlier research does not distinguish between interdependence and coupling, I argue that they are distinct concepts. The concept of coupling also makes it possible to use the NK model to study modularity, another important characteristic of technology search. Not only does coupling play an important role in mitigating the complexity catastrophe, it also plays an important role in uncovering interdependencies.

In the subsequent sections, I develop a model of technology search that incorporates the concept of coupling (i.e. both modularity and integration) and seek to show how coupling improves the process of technology search. In §3, I present the results from a simulation study that seeks to show that coupling improves the search on NK landscapes. The results from the simulation study guide the development of the hypotheses in §4. I also seek to show how coupling moderates the effects of experiential and cognitive search and thereby affects the malleability of a firm's knowledge base.

3 A SIMULATION BASED STUDY ON THE EFFECT OF COUPLING ON SEARCH ON AN NK LANDSCAPE

In this section, I discuss the effect of coupling on the search on an NK landscape. This simulation study builds on the work of Kauffman et al (1994), Kauffman (1995) and Levitan et al (1999). The basic idea in this study that modularity improves the search process for computationally complex problems has been demonstrated in a number of studies previously (for example, Cohen, 1981). However, to my knowledge, this is the first study that examines the effect of coupling between modular clusters on the search process. First, I show that near decomposability in the coupling matrix improves the search process compared to either no modularity or complete modularity. Then I discuss the reasons why this seems to occur.

Kauffman (1993:55) reports the mean values of the peaks on NK landscapes for various values of N and K. The key finding is that the mean value is highest for low values of K (K=2 to 4) and drops as K increases as a constant proportion of N. In subsequent work, Kauffman and his colleagues (Kauffman et al (1994), Kauffman (1995) and Levitan et al (1999)) extended the basic model to incorporate the "Divide to Coordinate" heuristic. In this heuristic, the system is divided into a number of clusters and the search for peaks is conducted in each of these clusters independently. Remarkably, the mean height of the peaks that are found increases when cluster size is between 1 and N. Kauffman and colleagues interpret this as evidence that the invisible hand of coordination works.

In this simulation study, I extend the above results. First, I reinterpret Kauffman and colleagues' findings in terms of coupling between clusters. The three systems they compare are shown in Figure 4. The number of clusters (J) is N in system A, 1 in system B, and between 1 and N in system C. In system A, search at each node is conducted selfishly, independent of all the other nodes. A move that increases the value of the focal node is accepted even when it reduces the values of other nodes in the system, which implies that coupling is zero. In system B, there is only one cluster and search is conducted at a global or system level. A move is accepted only if it increases the value of the system as a whole. Here, coupling is equal across all the nodes. In system C, search is conducted selfishly at a cluster level. A move is accepted if it increases the value of the cluster irrespective of the effect on other parts of the system. Here, coupling is equal to one within the cluster and zero between clusters. Kauffman et al (1994) find that system C reaches higher peaks on average than the other two systems. Note that even after the system is divided into clusters, there are a considerable number of interdependencies that cut across cluster boundaries.

In the current study, the effects of increasing the coupling between clusters on the mean value of the system are explored. Introducing coupling between clusters changes a fully decomposable system (system C in Figure 4) to one that is nearly decomposable (system D in Figure 4). Instead of specifying coupling for all pairs of nodes, I simplify by assuming that coupling is the same for all pairs of nodes within each cluster. Further,

L_J, the coupling within each cluster is set at 1. Coupling between pairs of nodes that belong to different clusters is replaced by coupling between the clusters, L_R, which is assumed to be the same between all clusters. When $L_R = 0$, coupling between clusters is zero. When $L_R=1$, equal weights are attached to both the focal cluster and all the other clusters, which is the same as saying that there are no clusters[21].

The mean values (for 1,000 simulations, at the end of 3,000 generations) are plotted against L_R (Figure 5) for N=12, K = 4, 6, 8 and 11 and different number of clusters[22]. The interdependencies are assumed to be with the immediate neighbors. Nodes are assumed to lie along a ring to avoid end effects. That is, for K=4, the 12th node is interdependent with nodes 10, 11, 1 and 2. Separate simulations show that similar results are obtained even when interdependencies are with randomly chosen pairs of nodes. At the beginning of each simulation, each configuration of elements is randomly assigned a value between 0 and 1.

As can be seen from Figure 5, a low coupling between clusters has a significant effect on the mean value obtained for K>=8. The system performs better when L_R is low and > 0 than when $L_R = 0$ (a fully modular system) or $L_R = 1$ (no clusters). As the number of

[21] L_R, the weight attached to the rest of the system can be higher than L_J, the weight attached to the group. Very interestingly, even such an altruistic search strategy results in higher system level values. The implications of such a search strategy are beyond the scope of this study. The search strategies can also differ across the groups, with some groups being more selfish than the others. Again, the implications of different search strategies across the groups are beyond the scope of this study.

[22] In these simulations, the first one-mutant move that meets the acceptance criterion is accepted. Similar results were obtained when the best one-mutant move was chosen with the main difference that the minimum K at which coupling has an effect is higher for best one-mutant move strategies.

clusters decreases, the optimal level of L_R decreases. However, this effect may disappear when larger clusters are further split into sub-clusters such that coupling between sub-clusters is higher than the coupling between clusters. This possibility will be examined in subsequent work. A very interesting feature of these results is that even when all nodes are interdependent with all the other nodes (K=11), dividing the system into clusters and providing coupling between clusters improves the outcomes of the search process. So, a nearly decomposable coupling matrix improves the search process even when the underlying structure of interdependencies is not nearly decomposable.

With respect to the standard deviation of mean value (Figure 6), two observations can be made. First, the standard deviation of the mean value increases as coupling between the clusters decreases for all cluster sizes (Figure 6). Second, for low values of L_R, standard deviation increases as the number of clusters increases. These increases in standard deviation provide pointers to the usefulness of low coupling between clusters, as discussed next.

To understand why a nearly decomposable coupling matrix improves the search process, I examine the number of peaks and their basins of attraction for different levels of coupling between the clusters. In Figure 7 (which is similar to Fig 2.8 in Kauffman, 1993), the value of a peak is plotted against the number of times that peak was attained with different starting configurations on the same landscape and for different values of L_R. The number of times a particular peak is attained is an approximation of its basin size (Kauffman, 1993). In the basic NK model (where search is based on system-level values, i.e. L_R=1), Kauffman (1993) points out that for low K (K<=8) the highest peaks also tend to have the largest basins increasing the probability that high peaks are found. As K increases relative to N, the basin sizes of the highest peaks become very small making it less likely that they are found. For larger K, the system reaches a certain peak (which on average is small for higher K) and gets stuck at that peak.

The reason why search with coupling between clusters increases the mean value is that the system does not get stuck to a poor peak (Kauffman et al, 1994). When search is conducted based on system-level values, the system will not move from a peak if a move reduces the system level value. When search is conducted based on cluster level values, moves that increase the cluster value are accepted even when they reduce the system value. Hence the system will wander away from a point that is a local peak for system search until it reaches a point that is a local peak for all clusters. As the coupling between the clusters decreases, the number of optima decreases (Figure 7) and their basin size increases. It also turns out that the average height of these peaks is higher (for L_R=0.08) than the average height of the peaks that exist for system search. When search is conducted at the cluster level, sooner or later, the search wanders into the basin of attraction of these peaks. Hence, cluster search leads to a higher system value.

A further important insight on the usefulness of coupling can be obtained by looking at the length of the adaptive walks and the percentage of adaptive walks that reach a local optimum. Length of an adaptive walk is the number of one-mutant moves attempted before a peak is reached. The larger the number of moves attempted, the farther is the system from its current position. So walk length represents the continuum between exploitation and exploration (Levitan et al, 1999). I show next that the mix between exploitation and exploration changes as the level of coupling between clusters increases. The usefulness of low coupling between clusters can be related to the balance between exploitation and exploration that it achieves, as discussed next.

When search is conducted at a system level, the system moves incrementally to a peak of the basin of attraction in which the system is initially located. After a peak is reached, one can search locally for neighboring peaks. However, even that potential is soon exploited and local search becomes increasingly ineffective. The general recommendation that is provided in such a situation is that one should make a long jump to a distant neighborhood to find new peaks through the process of exploration. However, the average height of peaks is low for high K landscapes. So, such long jumps will only find peaks that are, on average, inferior. In support of this argument, there is extensive evidence that such long jumps can have adverse effects including mortality (Gavetti and Levinthal, 2000). As such, firms get trapped to their existing peaks.

A way in which firms can combine local with distant search is by modularization or near decomposability. Changes made in the states of nodes within a cluster affect the contribution of nodes in a second cluster that are interdependent with the nodes in the first cluster. It becomes necessary to change the states of the nodes in the second cluster and this leads to a cascade of moves until a peak that is simultaneously optimal for all the clusters is found. So, even when search is conducted locally at the cluster level, the firm can experience a system wide exploration. For example, the Internet is leading to an economy wide exploration after starting off as a small-scale activity in government labs. The need for modularity is apparent here because it would not be possible for the economy to take a long jump – from no Internet use to full-scale use. A modular approach to Internet adoption at the level of the economy gives time to evaluate whether to make the change and if change is seen as desired, how businesses should be reconfigured to make use of the change.

The relative levels of exploitation and exploration depend on the structure of the coupling matrix. The length of the adaptive walk and the percentage of times that the system reaches equilibrium for various levels of coupling are shown in Fig 8. As can be seen, length of the adaptive walk increases as L_R decreases indicating that exploration increases as coupling between clusters decreases. When all the elements are coupled to each other (L_R=1) the system is restricted to exploitation, as seen by the short walk length (Figure 8a). When all the elements are decoupled and search at each node is conducted independent of the other nodes (L_R=0), the system does not reach a local peak quickly as seen by the large walk lengths. The increasing amount of exploration as L_R decreases is also the reason why uncertainty increases with decreasing L_R (Figure 6).

Also, some of these walks may never reach equilibrium (Figure 7b) in the time span considered in the simulations when L_R is very low or equal to zero. This suggests that there seems to be more exploration than is optimal at these levels of L_R. Levitan et al (1999) suggest that the optimal values are obtained when there is a balance between exploitation and exploration. Similarly, I suggest that the level of coupling that achieves the highest value is that level of coupling that achieves the "right balance" between exploitation and exploration.

To further characterize what this right balance between exploitation and exploration is, one can compare the number of times exploitation occurs with the number of times exploration occurs. More generally, one can plot the frequency with which an adaptive walk of a certain length occurs against the length of the walk. Following Kauffman (1993: 264) I generate adaptive walks of various lengths by changing the state of a randomly chosen node after placing the system at a peak (for that level of coupling). This process is repeated 5,000 times. The results are plotted on a log-log plot (Fig. 9, which is analogous to Fig. 6.10 in Kauffman (1993: 264)). As expected, the number of times exploration occurs is far less than the number of times exploitation occurs as seen by the negative slope of the line. This is consistent with the evidence that most technology search occurs through incremental innovations; occasionally, a few radical innovations occur. More interestingly, the line is nearly straight when coupling is near its optimal level (L_R=.08) and convex for coupling higher than the optimal level (L_R=1) and concave for coupling lower than the optimal level (L_R=.04). This implies that an increase in the level of exploration results in a proportional decrease (on a log-log scale) in the likelihood that the exploration will occur when coupling is near its optimal level. In the other two cases, there is a disproportionate decrease or increase (on a log-log scale).

Another way to characterize this balance between exploration and exploitation is by relating them to ordered and chaotic regimes (Levitan et al, 1999). Kauffman (1993) and Levitan et al (1999) show that the system performs best when it is near the phase transition between the ordered and chaotic regimes, also called as the edge of chaos (Kauffman, 1993). Here, non-completion of walks can be related to the presence of chaos. Incomplete walks begin to occur at L_R< 0.1 (Figure 9b). The optimal level of coupling is slightly lower at 0.08 indicating that at this level of L_R, the system seems to be poised at the edge of chaos. The importance of this balance between order and chaos has also been highlighted in the work of Eisenhardt and her colleagues (for example, Brown and Eisenhardt, 1997).

Finally, the balance between exploitation and exploration implies that values obtained at the end of adaptive walks would be the same whether they are exploitative or exploratory in nature. On the other hand, at high levels of coupling there is less exploration than required. This suggests that the returns to exploration will be higher and the values of walks that are exploratory in nature would be higher than the values of walks that are exploitative in nature. Similarly, when coupling between clusters is zero or very low there is more exploration than necessary and the returns to exploitation should be higher.

The above relationships were found in the simulation results. In Figure 10, the height of the peak achieved is plotted against the length of the adaptive walk for different values of coupling. The lines in Fig. 10 are the best-fit lines drawn through points representing the height of peaks for 5,000 simulations. Each walk is initiated by changing the state of a randomly selected node after placing the system at a local optimum. Fig. 10 shows that when coupling between clusters is high, the line has an upward slope indicating that longer walk lengths are more useful at higher values of coupling. At the optimal level of coupling between clusters (~ 0.08), the line is flat indicating that values associated with exploitative and exploratory walks are equally useful at this level of coupling. As exploration crowds out exploitation at very low levels of integration, one can expect exploitation to be more useful than exploration at this level of integration. However, for very low values of coupling (~ 0.04), exploration and exploitation seem to be equally useful (Figure 10). Further analysis is required to understand why the expected relationship is not observed at very low levels of coupling.

Conclusion

The results from the simulation study show that near decomposability in the coupling matrix improves the search process on NK landscapes even when interdependencies are pervasive. This improvement seems to occur because near decomposability places the system at the edge of chaos where it can achieve the balance between exploitation and exploration. Accordingly, at the optimal level of coupling, exploitation and exploration were found to be equally useful.

4 EMPIRICAL HYPOTHESES

In this section, I develop hypotheses about the impact of the structure of a firm's knowledge base on its technology search, to be tested in an empirical context. In §4.1, I discuss why the structure of a firm's knowledge is likely to be nearly decomposable. In terms of coupling, this has two implications. First, knowledge clusters that have high coupling within themselves are likely to exist. Second, a low level of integration is likely to exist between these clusters. Then I discuss the performance implications of near decomposability and propose a curvilinear (inverted U) relationship between level of integration between clusters and usefulness of inventions.

In §4.2, I discuss the role of structure in changes that occur in a firm's knowledge base. I first discuss the mechanisms through which a knowledge base changes and then discuss the effect of structure on these mechanisms. The mechanisms of change that I consider are use of knowledge about past successes and use of scientific knowledge. While the first mechanism represents experiential search, the latter represents cognitive search. I then propose that firms with an intermediate level of coupling are also in a better position to use these two mechanisms of change. The proposed hypotheses are summarized in Table 7 and illustrated in Figure 11.

4.1 Structure of a firm's knowledge base

When the landscape metaphor is applied to technology search, the landscape represents the space of technological possibilities. Each point on the landscape represents a particular configuration of all knowledge elements i.e. each point represents an invention[23]. The value associated with a configuration represents the usefulness of the invention. In this study, a patent represents an invention and its usefulness is measured by the number of times it is subsequently cited. The problem of searching for useful inventions can now be represented as the problem of finding peaks associated with high values.

Given that there are a very large number of elements, the first issue that has to be decided is which elements should be combined. Initially, let us assume that the firm can combine only those knowledge elements that it has accumulated. Later on, this assumption can be relaxed to examine the effect of other sources of knowledge, specifically knowledge acquired through science or imitation. The knowledge elements that the firm has accumulated can be approximated by its patent portfolio, which includes its own patents as well as the patents that it had cited (Ahuja and Katila, 2001). The firm now has to search for configurations of these knowledge elements that are associated with high values.

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[23] It should be noted that most points on the landscape would not be "inventions" in the common sense of the word because they would turn out to be useless.

Let us first consider trial-and-error search, i.e. search in which the elements whose states are changed are chosen randomly. The firm can determine the value of any new configuration after it has been put together. Whether it will accept this new configuration or not will be based on a decision criterion. The simplest criterion is that the firm accepts the new configuration if its value is higher than the value of the old configuration. Introducing coupling into the system changes the decision criteria, as discussed shortly. From the new configuration, the firm searches for other configurations and repeats the process until it ends up at a local peak or a useful invention. Starting from different initial configurations or taking different paths from an initial configuration, the firm can generate more than one invention.

As discussed before, the firm can move to a new configuration by changing a certain number of nodes, the number varying from 1 to all the elements. However, when one does not possess knowledge about the features of the landscape and searches through trial-and-error search, one is restricted to considering moves that involve very few mutations. If too many mutations are considered at one time, the firm is more likely to end up at a distant neighborhood with peaks which on average will be low for a high K landscape. Even when one possesses knowledge of the landscape, such knowledge is never complete. Hence, search through one-mutant or few-mutant moves is more likely than search than n-mutant moves. However, when one-mutant moves are considered, the system reaches a local peak very quickly, especially on high K landscapes. Also, the average height of such peaks is also low on high K landscapes. Structuring the knowledge base through coupling between elements can improve the search process as discussed next.

4.1.1 Near-decomposability of a firm's knowledge base

The results from the simulation study presented in §3 suggest that when modularity accompanied by integration exists in the structure of the system that represents the firm's knowledge elements, there is an improvement in the outcomes of the search process. The reasons are as follows. First, modularity implies that the firm is no longer searching across all its elements simultaneously. The search process can be divided across various clusters, which has the advantages of both simplicity within a cluster and simultaneity across clusters.

Dividing the knowledge base into clusters can also be seen as the process of differentiation (Lawrence and Lorsch, 1967) or using the splitting operator (Baldwin and Clark, 2000). Ignoring the interdependencies that exist between elements belonging to two different clusters makes it simpler to search within each cluster. It is easier to search for good configurations for the elements within the cluster because of the reduced number of elements under consideration. For this reason, Thompson (1967) suggests that the technical core of a firm should be buffered to achieve technical rationality. The process of splitting into clusters also leads to specialization. The technical personnel of the firm do not need to know all the knowledge elements of the firm. They can restrict themselves to a single cluster and increase their expertise in that area.

Second, as discussed before, firms are not aware of the true underlying interdependences and an important aim of technology search is to uncover these interdependencies. Splitting into clusters has the further advantage that it makes the task of uncovering interdependencies easier[24]. It is easier to observe the relationships between a set of variables when the effects of other variables are not considered[25]. Research in cognitive psychology shows that restricting the scope of a problem can make it easier to notice the unexpected (Goldenberg et al 1999) and uncover the "true" underlying relationship within the cluster. Obviously, the "true" relationships between the entire set of variables would be better understood if it were possible to handle all the variables simultaneously. However, computational complexity implies that inventors have to set a boundary at some stage or the other and it is this boundary that results in the formation of clusters.

Third, modularity can lead the firm to exploration. When changes are made to the states of nodes within a cluster, then sometimes, these changes affect the contributions of nodes that are in a second cluster. The changes made in the first cluster can lead to changes in the second cluster and these changes can result in further changes in other

[24] For instance, when a set of 10 elements is divided into two sub-sets of 5 elements each, the number of relationships to be considered drops from 1,024 (2^{10}) in the entire set to 32 (2^5) in each set.
[25] The effects of other variables are controlled, with varying levels of success.

clusters and so on. When such walks traverse cluster boundaries, the search moves away from the local neighborhood of the current configuration and leads to exploration of distant neighborhoods. Here, it should be noted that walks that cross cluster boundaries take the system away to a distant neighborhood only when boundaries are well defined, as discussed later. So, firms can explore distant neighborhoods even through local search when modularization is present. When modularization is absent, local search pulls the firm back to the starting local peak, its competency trap (Levitt and March, 1988).

However, there is a legitimate concern that such independent searches in each cluster can make the system unstable with changes in one cluster negating the effect of changes in other clusters (Levinthal and March, 1993; Baldwin and Clark, 2000). The results from the simulation study also show that a perfectly modularized system can end up on unproductive and very long adaptive walks (Fig. 8). These long unproductive walks can be constrained by providing coupling between clusters as discussed next.

While splitting the system into clusters has a large number of advantages, prior theory strongly suggests that differentiation should be accompanied by integration (Lawrence and Lorsch, 1967; Galbraith, 1973; Baldwin and Clark, 2000). This is accomplished through the process of coupling between clusters. This makes the matrix of couplings between the knowledge elements nearly decomposable – coupling within clusters will be high compared to the coupling between clusters. Such coupling leads to the following improvements in the search process. First, while ignoring interactions that exist across clusters improves the search within a cluster, it also limits the search process. A constraint that exists when search is confined to the cluster may disappear when elements of other clusters are considered. Ignoring the interactions across clusters may thus lead to under exploitation of an opportunity. These limits on search are increasingly felt as the technological potential of the cluster is exhausted through exploitation. So, when changes in a cluster are made after considering the effect on nodes in another cluster, that is when the clusters are coupled, the search process can be improved.

Second, coupling between clusters also has a positive effect on discovering the “true” level of interdependencies. This would happen if an interaction between two clusters previously assumed to be weak turns out to be more important. A firm is more likely to be aware of this interaction if it has provided for this interaction in its coupling matrix. Hence, coupling between clusters makes it easier to uncover interdependencies that exist across clusters and thus ensures that the firm is able to redefine the partitioning of its knowledge system when necessary. I will next consider the effect of the level of coupling or integration between clusters on the search process. I will consider three different levels of integration between clusters: zero or very low integration, an intermediate level of integration and a high level of integration.

The results of the simulation study (§3) suggest that a certain level of coupling between clusters achieves the necessary balance between exploitation and exploration and leads to good inventive outcomes. The results from the simulation model cannot be applied to the problem of technology search directly. When the states of nodes in a cluster change, the contributions of nodes in a second cluster that are interdependent on these nodes also change even when coupling between the two clusters is zero. In the simulation model, it was assumed that the effect is immediately noticed and the inventors in the other cluster factor this into their search. Results from the simulation model show that when coupling is zero or at a very low value, adaptive walks tend to be very long.

However, in technology search inventors in the second cluster may not be aware of the changes in the contributions of their nodes brought into effect by changes in the first cluster because lack of coupling may be associated with lack of communication (Glassman, 1973). As a consequence, inventors in the second cluster may not make the necessary changes in their own search and may be missing out on inventive opportunities. So when coupling is zero or very low between clusters, the long adaptive walks as predicted by the simulation model may not actually occur. A similar analogy exists in the case of modular design or products. A complete modularization or zero coupling between modules implies that the inventive search in each module is carried on independent of the search in other modules. Baldwin and Clark (2000) point out that complete modularization can result in a long cascade of changes that may never reach equilibrium. To prevent such long walks, modularization includes specification of design rules that inventors in each module should adhere to. These design rules ensure that long adaptive walks that cut across modules do not occur. Consequently, when long adaptive walks are avoided, the firm is likely to restrict itself to exploitation and miss out on any advantages that exploration may provide.

When coupling between clusters is high, or equivalently when clusters do not exist adaptive walks will be short in length because when coupling is high between clusters inventors across the two clusters are aware of the changes that are occurring in the other cluster and are then likely to keep in mind these changes when conducting their own search. The negative side of being aware of the changes in the other clusters is that inventors would then tend to make only those changes in their own cluster that will have a positive effect on the second cluster as well. This would reduce the number of possible moves they consider because many moves that have a positive effect on the first cluster may have a negative impact on the second cluster. Consequently, they tend to resist exploratory moves that will take them away from their current local peak.

At low-to-intermediate values of coupling between the clusters, decision-makers are aware of the interaction effects across clusters but achieve the right balance between ignoring the effects that occur in other clusters and giving them too much importance. At the same time, they are also likely to allow the adaptive walks or exploration to occur. This leads to the following hypothesis:

> **Hypothesis 1:** The level of exploration in a firm's inventions is related to the integration between its clusters of knowledge in a curvilinear (inverted-U shaped) manner.

The results from the simulation study show that the mean value of the peaks found at the end of the search is dependent on the level of integration (Fig. 5) and is highest for a low-to-intermediate level of integration. So, firms that have this optimal level of integration are likely to generate useful inventions. If all firms have a nearly decomposable structure and if all achieve the optimal level of coupling, then there would be no performance differences between firms with respect to their technological search. I next explore why performance differences are likely to exist.

It can be seen from Figure 5 that the mean value of the peaks is highly sensitive to the level of coupling between clusters in the region where coupling is optimal. This implies that it would not be easy for firms to determine the level of coupling that would lead to the most useful inventions. It is easy to see why firms would err on both sides and choose higher than optimal levels of differentiation or integration. When different project groups are working on different clusters, integration between clusters would not happen naturally. The firm may need to set up integration mechanisms and these mechanisms can be expected to have varying levels of success. Making the coupling matrix nearly decomposable also implies setting up boundaries between previously integrated elements of knowledge. Once a certain set of knowledge elements have a high level of coupling, organizational inertia may make it difficult to bring about the process of differentiation. Also, ignoring interactions between clusters of knowledge elements as required in the process of differentiation would also be counter-intuitive to many managers. Consequently, across the spectrum of firms, one can expect to see firms that have got it right (and reap the benefits in terms of generating useful inventions) and others that have too much or too little integration. This leads to the following hypothesis:

> **Hypothesis 2:** The usefulness of a firm's inventions is related to the level of integration between its clusters of knowledge in a curvilinear (inverted-U shaped) manner.

4.2 Changes in a firm's knowledge base

I look at the changes that occur in the knowledge base of a firm for two reasons. First, firms need to change their knowledge base to ensure that their knowledge base includes some of the new knowledge that is being generated. They also need to change their knowledge base because the potential for generating inventions from an unchanging knowledge base decreases over time (Ahuja and Katila, 2002). For this reason, it is important to know how a firm's knowledge base changes over time and examine the factors that improve or hinder this process.

Second, the previous hypotheses discussed the structure of couplings in a firm's knowledge base. They imply that coupling between some elements should be high and coupling between some other elements should be low. But, how does a firm know which particular coupling has to be high and which coupling has to be low? I argue here that this decision is based on the current guesses that the firm has on the interdependencies such that the firm is able to generate useful inventions that make use of the knowledge about these interdependencies. Also, this decision on which two elements should be coupled also reflects the firm's attempts to uncover new interdependencies or improve guesses about interdependencies. To test these two basic arguments, I look at how the knowledge base of a firm and its structure change over time. I first discuss the reasons why a firm's knowledge base is likely to be rigid and then discuss how such rigidity can be minimized.

Prior research shows that firms engage in local search in the space of possible states of the elements that they recombine (Stuart and Podolny, 1996; Patel and Pavitt, 1997). One can extend the logic to the case of the structure of a knowledge base and argue that firms engage in local search in the space of possible structures as well. Henderson and Clark (1990) point out that changing the architectural knowledge of a firm is difficult because it is difficult to change the firm's organization systems and information channels in which the architectural knowledge is embedded. So, any changes that occur in the architectural knowledge are likely to be small. A similar argument can be applied to the case of the structure of a knowledge base as well. Structures at adjacent times would be very similar due to the difficulty in changing the systems and information channels.

4.2.1 Malleability of the knowledge base

However, near decomposability in the structure can increase the malleability of the structure and provide the capacity for adaptive change, as discussed next. First, I will discuss the mechanisms through which structure changes and then discuss how firms that have knowledge bases that are nearly decomposable are in a better position to make use of these mechanisms.

Broadly speaking, any changes that occur in the knowledge base of a firm (knowledge stock) would be a result of knowledge generation (knowledge flows). These changes can be expected to occur in response to the changes in perceived interdependence or in the process of search for previously unknown interdependencies. Previous work suggests that there are a number of sources of new knowledge including knowledge of successes and failures, scientific knowledge (Rosenberg, 1982; Klevoric et al, 1995), suppliers, users (von Hippel, 1988), alliances (Ahuja, 2000; Ahuja and Katila, 2001), and mobility of inventors. In this dissertation, I focus on the first two sources of knowledge, which represent experiential and cognitive search respectively. Knowledge of successes and failures is an essential part of experiential search. Application of scientific knowledge is an important way in which cognitive search is conducted.

4.2.2 Experiential search and changes in the structure of a knowledge base

While changes in the elements of a knowledge base can occur due to both local and distant search, changes in the structure are more likely to be an outcome of distant search. Local search or exploitation works well when interdependencies are reasonably well understood. Naturally, the scope for discovering new interdependencies is limited. In contrast, distant search or exploration occurs when search cuts across cluster boundaries and leads to changes in the states of elements across clusters. Some of these distant searches would be based on knowledge of interdependencies that is relatively less complete. Hence, distant search has the potential for uncovering new interdependencies.

When does a firm realize that it needs to update its guesses about interdependencies? One way in which this would happen is when a firm does trial-and-error search or experiential search and one of the trials leads to a successful invention. Such knowledge of a success would alert the firm to the fact that the interaction between the two elements is stronger that was previously assumed. Consequently, the firm is likely to increase the coupling between the two elements and achieve a change in the structure of its knowledge base.

> **Hypothesis 3a:** The change in coupling between two knowledge elements is related to the success of prior exploratory inventions that combine these two elements.

An increase in integration will naturally occur because the successful invention by definition is a patent that is cited by many later patents, which presumably would also be combining elements across the two clusters. So the above measure of increase in coupling has to be based on patents that are not direct descendants of the original exploratory invention. The hypothesis would still hold, as the usefulness of the first invention would push the firm to search for other inventions that combine these two elements.

4.2.3 Cognitive search and changes in the structure of a knowledge base

A second way in which a firm recognizes the need to update its guesses on interdependencies is when it performs cognitive search, for example, in the form of using scientific knowledge. Previous research suggests that science plays an important role in expanding the set of elements that are available for recombination (Ahuja and Katila, 2002). Further, science provides a cause-and-effect relationship that informs the firm of potentially valuable recombinations (Henderson and Cockburn, 1994; Fleming and Sorenson, 2001b). Both these arguments suggest that firms can reach a higher level of understanding about the "true" level of interdependence between knowledge elements by using scientific knowledge. Such new knowledge about underlying interactions would result in a change in the structure of the knowledge base. These changes are likely to higher for those couplings that are low to begin with. So, inventions that use scientific knowledge are more likely to be exploratory than exploitative. Even when science is used for within cluster exploitative inventions, it could be playing a role in reorientation of the partitioning that is present within the cluster. But, the importance of science is higher at higher levels of analysis i.e. science is more used when reorienting coupling between clusters than when reorienting coupling between sub-clusters. The above discussion leads to the following hypotheses:

> **Hypothesis 3b:** The change in coupling between two knowledge elements is related to the use of science in exploratory inventions that combine these two elements.

Hypotheses 3a and 3b are restricted to changes in coupling between technology classes that have a non-zero coupling in the previous time period. Technology classes that are used in the later time period but not used in a previous period also involve a change in coupling but such a change in coupling is not based on a firm's observations of the success of its own patents or use of scientific knowledge in exploratory inventions and involves other sources of knowledge which are not covered in this study. It should be noted that for hypotheses 3a and 3b, analysis is at the level of technology class pairs. For all the other hypotheses, the analysis is at the level of the firm.

4.2.4 The role of past structure on the changes in the structure of a knowledge base

Firms are likely to differ in their ability to accomplish changes in their structure. I argue that this ability is related to the integration between a firm's knowledge clusters. That is, the structure of a knowledge base can affect the changes that occur in itself. Hypothesis 1 predicts that firms that have an intermediate level of integration between clusters are more likely to generate exploratory inventions. Since, exploratory inventions are more likely to lead to changes in structure, firms that generate more exploratory inventions would be in a better position to accomplish changes in structure. Further, one can argue that they also have the absorptive capacity (Cohen and Levinthal, 1990) to integrate the new knowledge that is generated with their existing knowledge base because of the presence of coupling across the clusters. Galunic and Eisenhardt (2001) present evidence on the importance of coupling across clusters for change, though in a different context. They show that relatedness between the modular structures (i.e. business divisions) in a firm facilitates charter recombinations[26].

Hypothesis 1 also predicts that firms that have integration that is above or below the optimal level are likely to generate fewer exploratory inventions. So these firms are less likely to generate inventions that will affect their perceptions of the underlying interactions. However, they can observe the inventions of their competitors and then make the necessary changes. This is not likely to be easy for two reasons. First, Tratjenberg et al (1997) show that firms that develop an invention are able to recognize the potential for further development earlier than other firms. So firms that do not generate exploratory inventions are unlikely to immediately recognize the usefulness of their competitor's exploratory inventions or the implications of such inventions. Second and more importantly, even when they recognize the importance, imitation will not be easy because firms with very low coupling (i.e. coupling below the optimal level) will

[26] Relatedness implies that coupling is likely to exist between the business divisions.

lack the absorptive capacity to make use of this knowledge. Firms that have high integration between clusters achieve this high integration at the cost of the variety in the knowledge elements that they possess. So, firms that have high integration between clusters may also lack the absorptive capacity to make use of this knowledge unless the exploratory invention falls in their narrow range of knowledge. To conclude, firms that have an intermediate level of integration between their clusters are more likely to accomplish changes in structure than firms that have integration that is above or below the intermediate level. This leads to the following hypothesis:

> **Hypothesis 4a:** The extent of changes that occur in the structure of a firm's knowledge base is related to the level of integration between its clusters of knowledge in a curvilinear (inverted U-shaped) manner.

Now, I look at the effect of scientific knowledge at the level of the firm. Following Hypothesis 3b, one can argue that firms can accomplish changes in the structure of their knowledge base when they use scientific knowledge in their inventions. So, I hypothesize:

> **Hypothesis 4b:** The extent of changes that occur in the structure of a firm's knowledge base is related to the firm's use of scientific knowledge.

Again, firms that have an intermediate level of coupling are likely to be in a better position to use scientific knowledge to change their structure because of their higher absorptive capacity (Cohen and Levinthal, 1990).

> **Hypothesis 4c:** The effect of use of scientific knowledge on the extent of changes that occur in the structure of a firm's knowledge base depends on the level of integration between its clusters of knowledge in a curvilinear (inverted U-shaped) manner.

5 METHODS AND MEASURES

5.1 Empirical setting: Semiconductors

The empirical setting for this study is the worldwide semiconductor industry. Longitudinal data from 1981 to 1999 was used. A number of reasons motivate the choice of semiconductors as the setting for the study. First, the high R&D intensity of semiconductors implies that technology search is of considerable importance in this industry. Second, the industry is also characterized by incessant technology change. Since some of the hypotheses examine the changes in a firm's knowledge base, an industry that has witnessed considerable technological change is an appropriate setting for the study. Third, as the semiconductor industry has a high reliance on science (Klevoric et al, 1995), it provides an opportunity to study the effects of cognitive search.

The key dependent and independent variables are based on patents granted by the US patent office (USPTO). While patent and citation based measures have certain limitations, a number of studies have demonstrated their validity as measures of invention (for example, Narin, Noma and Perry, 1987; Hall, Jaffe & Trajtenberg, 2000). Further, since this study is limited to a single industry, differences in patenting and citation rates across industries, a key problem with using patent data (Hall, Jaffe & Trajtenberg, 2001) is not present here.

Each patent provides information on the firm (or inventor) to which the patent has been assigned, its year of application and citations to previously granted patents. Further, USPTO assigns each patent to a 3-digit technology classes. There are about 400 technology classes to which a patent can be assigned. This classification system is being continuously updated as the technologies continue to evolve. I used the classification that was current on 31st December 1999 (Hall et al, 2001).

Several studies (for example, Jaffe, Trajtenberg and Henderson, 1993; Stuart & Podolny, 1996) have shown that patents and the citations to patents can be used to study the search behavior of firms. I follow a similar approach and examine the citations made by the firm's patents. Each cited patent has an assigned class and in the following discussion I refer to the class of the cited patent as the cited class.

As this study used patents for building both dependent and independent variables, firms that did not patent were excluded. I identified 115 semiconductor firms across North America, Europe and Asia. Patents belonging to these firms and their subsidiaries were identified. Information on subsidiaries was collected from *Who Owns Whom* Corporate Directories and Lexis-Nexis news reports. Data on control variables was obtained from *Compustat*, *Japan Company Handbooks* and Lexis-Nexis. Lack of data on performance and firm size reduced the sample to 85 firms. As discussed later, I also ran all my models on the entire sample of 115 firms while excluding size related data.

I used the data on technology classes to identify semiconductor patents among the patents granted to the semiconductor firms in the sample by the following method. I ranked all technology classes by the number of semiconductor firms that had a patent belonging to that technology class and then assumed that the top 30 classes by rank can be considered as semiconductor classes. I also considered an alternative method for identifying semiconductor classes in which I identified 12 of the above 30 classes as semiconductor classes based on the description of technology classes provided by USPTO. In both these cases, I placed no restriction on the number of cited classes[27]. Using 30 classes resulted in 51% of all patents that were assigned to the semiconductor firms in the sample being identified as semiconductor patents. The corresponding figure was 28% when 12 classes were used.

5.2 Variable definitions and operationalizations

Usefulness of inventions ($Usefulness_{i,t}$)

The number of citations that a patent receives is a significant predictor of the value or usefulness of a patent or invention (Albert, Avery, Narin & McAllister, 1991; Harhoff, Narin, Scherer & Vopel, 1999; Hall et al, 2001). Usefulness of inventions, at the firm level, is measured as the sum of number of citations that each of the firm's patents in year t receive in subsequent years till 1999. Consistent with the literature, I use the date of application for a patent and not the date when it was granted. I control for number of

[27] The data shows that the number of cited classes is over 200 for some firms when the number of semiconductor technology classes is 30.

patents that the firm has received in year t as the number of citations received is highly correlated with the number of patents.

Measuring coupling between knowledge elements

The coupling between the knowledge elements of a firm's knowledge base is approximated by the recombinations that exist in its patent portfolio. The underlying assumption is that if firms jointly search across two elements, that is, when the two elements are coupled, they are likely to generate an invention that repeatedly recombines these two elements. Reversing the logic, I consider that a repeated recombination of two elements can be taken as an indicator that the two elements are coupled. A firm's knowledge base or patent portfolio in year *t* consists of all the patents that the firm has accumulated during *t-3* to *t-1* years. To ease calculations, the technology classes that a firm cites are assumed to be the elements in the firm's knowledge base[28]. Technology sub-classes and patents represent the sub-elements of knowledge. The knowledge base in year *t* (comprising of patents from *t-3* to *t-1*) is used in generating inventions or patents in year *t*. The coupling between technology classes *j* and *k* for firm *i*, $L_{i,\, j\text{-}k,\, t\text{-}3 \text{ to } t\text{-}1}$ is calculated as

> $L_{i,\, j\text{-}k,\, t\text{-}3 \text{ to } t\text{-}1}$= Number of patents in which patents belonging to the two technology classes are cited together (If patent 1 cites patent 2 belonging to class

[28] If technology sub-classes or patents are taken as elements, then the number of elements in a firm's knowledge base will be large. This makes the task of measuring integration between clusters difficult.

j and patent 3 belonging to class *k*, then patent 1 is counted)/ Number of patents in which either class *j* or class *k* are cited (see Figure 12 for an illustration).

The coupling matrix, $\mathbf{L}_{i,\ t\text{-}3\ to\ t\text{-}1}$ consisting of $L_{i,\ j\text{-}k,\ t\text{-}3\ to\ t\text{-}1}$ for all pairs of elements represents the structure of the firm's knowledge base. This coupling matrix is used to measure the integration between clusters as discussed next.

Integration between clusters ($\text{Integration}_{i,\ t\text{-}1\ to\ t\text{-}3}$)

I used two alternative conceptualizations for this variable both of which are based on clustering coefficient, a concept used in the literature on complex networks (Watts & Strogatz, 1998; Barabasi, 2002). It is useful to visualize the structure of a firm's knowledge base as a network while measuring integration between clusters (see Figure 12 for an illustration). In this network, cited technology classes represent nodes and coupling between two classes represents a tie between the two nodes. The level of coupling represents the strength of the tie.

Clustering coefficient for an element or a node with k_i ties is defined as

$$CC_i = \frac{n_i}{\frac{k_i \times (k_i - 1)}{2}},$$

where n_i is the number of ties between the k_i neighbors of i. The denominator is the maximum number of ties that are possible between the k_i neighbors of i and the numerator is the actual number of ties that exist. Clustering coefficient for the network, CC, is CC_i averaged over all nodes (see Figure 12 for an illustration). A high clustering coefficient indicates that the system can be decomposed into clusters. A low clustering coefficient implies that clusters cannot be identified.

As defined in the current literature, the definition of clustering coefficient does not take the strength of a tie into account. The measure of integration between clusters that I built for this study is a modification of clustering coefficient that takes into account the strength of ties between nodes. First, I classify ties between nodes as strong or weak ties based on whether tie strength is greater or less than a prescribed cutoff value. I will discuss shortly how this cutoff value is determined. Second, I identify those nodes that can be considered as within cluster neighbors and across cluster neighbors for each node in the network[29] by a method that I will discuss later. Then, for each node I calculate its integration with neighboring nodes outside its cluster as

$$Integration_{node} = \frac{h+w}{\frac{g \times (g-1)}{2} + g}$$

where $h =$ number of neighboring nodes which are outside the focal node's cluster

$w =$ number of ties between neighboring nodes that are outside the focal node's cluster

$g =$ number of all nodes to which focal node is connected such that $\frac{g \times (g-1)}{2}$ is the maximum possible number of ties between the nodes to which focal node is connected. Finally, integration between clusters for the entire network is measured as a

[29] A neighbor is another node with which the focal node has a tie.

weighted sum of the integration for each node, with the percentage of patents that cite each node (i.e., class) as the weight (see Figure 12 for an illustration).

I used the following procedure to determine the cutoff value for classifying ties as strong or weak. Using a single value of coupling as a cutoff across all patent portfolio sizes is not appropriate as the median level of coupling (among all couplings greater than zero) in a patent portfolio depends on the size of the patent portfolio to a large extent. This decrease in the median value can be a true effect of size, which implies that in larger networks nodes are relatively weakly connected as compared to smaller networks. On the other hand, it can be an artifact of the measurement process. For each firm's knowledge network, one can assume that each class pair $i-j$ will contain a certain proportion (p_{ij}) of the total number of patents in the patent portfolio. So, the number of patents in each class pair can be calculated as number of patents in patent portfolio $\times\, p_{ij}$. This number will be small if number of patents in patent portfolio is small or if p_{ij} is small. Since patents are count variables, any value less than 1 will imply that no patents will belong to that class pair. Consequently, the number of nodes in a firm's knowledge network will be small when number of patents is small, even when p_{ij} is independent of size. In contrast, when the size of the patent portfolio is large, the number of nodes is much larger. As the number of nodes increases, the number of ties for each node increases, which in turn decreases the value of coupling between any two nodes. To remove this effect of size, I estimated the median value of coupling as a function of the size of the patent portfolio and time then assumed that this median value is the cutoff that is comparable across patent portfolios of different sizes for classifying ties into strong and weak ties. A log-log or power relationship proved to be a better fit than linear, exponential or log relationship. The estimating equation is

$$\text{Log (median value)} = 0.30443 - 0.00403 \times (\text{year-}1974) - 0.52853 \times \log(\text{number of patents in patent portfolio})$$

(R-squared=0.93)

I used two alternative methods to identify which neighboring nodes can be considered to be within cluster for each node. In the first method, I considered two nodes to be within the same cluster if one of the following conditions was satisfied:

1. They have a strong tie between them and there is at least one common node to which both are tied[30].
2. They have a strong tie between them and both nodes do not have any other ties at all.
3. They have a weak tie and there exists at least one node to which both are strongly tied.

All other ties are classified as weak ties. In the second and simpler method, I consider two nodes to be in the same cluster if they have a strong tie. I used the second method to test the sensitivity of the results to the first conceptualization.

[30] A strong tie between two nodes that have neighbors but not any common neighbors is still considered as an across cluster tie.

It should be noted that in both these approaches, cluster relationships are not transitive. That is, if node A and node B are in the same cluster and node B and node C are in the same cluster, then it does not follow that node A and node C are in the same cluster. So, this measure results in "fuzzy" clusters and avoids the problems associated with identifying precise cluster boundaries.

Exploratory inventions

An exploratory invention is characterized by search in a distant neighborhood that results in changes in the states of a number of nodes. As discussed before, when nodes from different clusters are combined, that is when a boundary is crossed, the firm is more likely to reach a distant neighborhood. The boundary can be internal or external to the firm. For example, an internal boundary can exist between knowledge clusters, between sub-units or between geographical locations. External boundaries that can be spanned include firm and industry. This study is limited to examining the effect of spanning the boundaries of knowledge clusters. I look at the cited classes for each invention or patent for firm *i* in year *t* and assume that the patent represents an instance of a tie between all pairs of cited classes. To measure boundary spanning, I measure the percentage of ties between classes that can be considered as across cluster ties i.e. ties between classes that are not within the same cluster[31]. I refer to this percentage as the across tie ratio for a patent in subsequent discussion.

However, boundary spanning is more likely to result in exploration when the boundary is distinct. That is, when integration between two knowledge clusters is high, boundary spanning may not always result in exploration. So, all inventions that combine knowledge elements across clusters are not likely to be exploratory. One has to make a further stipulation that the states of at least some knowledge elements should also be changing if the invention is to be considered as an exploratory invention. One good indicator that a knowledge element has changed states is that a new sub-element (technology sub-class) from an existing knowledge element (technology class) is being used for the first time. So, exploratory patents are defined as those inventions in year *t* that satisfy three criteria: a) they have to cite a sub-class which the firm has not cited during *t-3* to *t-1* years, b) at least half the ties between the technology classes cited by the patent can be considered as across cluster ties[32], i.e. across tie ratio is greater than 0.5 and c) no new technology classes are cited by the patent. The third criterion is required because the type of exploration that is considered in the study is limited to boundary spanning across existing knowledge clusters and a new technology class is not

[31] Whether two classes are in the same cluster or not is determined by the couplings that exist in the firm's patent portfolio.
[32] I test the sensitivity of the results by considering a more stringent criterion (at least 75% of the ties between the technology classes cited by the patent can be considered as across cluster ties) and a less stringent criterion (there is at least one tie between the technology classes cited by the patent that can be considered as an across cluster tie).

part of an existing knowledge cluster. The above definition of an exploratory patent implies that patents that combine classes that belong to the same cluster are not considered exploratory even when they cite a new sub-class. Such patents are exploratory to the cluster but not the firm. Patents that are not exploratory will be considered as exploitative patents.

Percentage of exploratory inventions ($\text{Percent\_Exploratory}_{i,t}$)

Percentage of exploratory inventions is a measure of the level of exploration in a firm's inventions.

$\text{Percent\_Exploratory}_{i,\,t}$ = Number of firm *i*'s exploratory patents in year *t*/ Total number of firm patents in year *t*.

Success of exploratory inventions ($\text{Success\_Exploratory}_{i,\, j\text{-}k,\, t\text{-}3 \text{ to } t\text{-}1}$)

This variable is used in Hypothesis 3a which considers changes that occur in the coupling between technology classes. The success of exploratory inventions is measured by the average citation rate of exploratory patents that cited a class pair. Average citation rate is calculated as the number of citations received by exploratory patents that cited a class pair in a six year period subsequent to the patent grant date divided by the number of such patents.

Use of scientific knowledge ($Sci\_Usage_{i,\, j\text{-}k,\, t\text{-}3 \text{ to } t\text{-}1}$)

I assume that a patent is based on scientific knowledge if it cites a non-patent reference (Trajtenberg, Henderson & Jaffe, 1997). A firm's Sci_Usage_i is measured as the percentage of patents in a firm's patent portfolio that cite a non-patent reference.

Average use of scientific knowledge ($Perc\_Science_{i,\, j\text{-}k,\, t\text{-}3 \text{ to } t\text{-}1}$)

This variable is used in Hypothesis 3b which considers changes that occur in the coupling between technology classes. The average use of scientific knowledge for a technology class pair was measured as the percentage of patents that cited a non-patent reference among those that cited the technology class pair.

Changes in coupling between elements ($Increase\_L_{i,\, j\text{-}k,\, t}$, $Decrease\_L_{i,\, j\text{-}k,\, t}$)

Hypotheses 3a and 3b discuss the effects of experiential and cognitive search on changes in the coupling between elements. I consider only a significant increase or decrease in coupling such that changes in coupling are comparable across patent portfolios of different sizes. A significant change in coupling was defined as change in coupling between two time periods that exceeds one quartile. I estimated the 25th percentile and the 75th percentile value of coupling as a function of the size of the patent portfolio and time. The estimating equations are:

$$\text{Log}\,(25^{th}\text{ percentile}) = 0.13610 - 0.01065 \times (\text{year}-1974) - 0.59788 \times \log\,(\text{number of patents in patent portfolio})$$

$(R^2=0.93)$

$$\text{Log (75}^{\text{th}}\text{ percentile)} = 0.57673 - 0.00081155 \times \text{(year-1974)} - 0.46515 \times \text{(number of patents in patent portfolio)}$$

$(R^2=0.90)$

The coupling for each class pair can be placed in one of four quartiles in both the previous and later time periods. I consider that a significant increase in coupling has occurred when the coupling for a class pair changes from a) first quartile in the previous time period to the third or fourth quartile in the later period or b) from second to fourth quartile and a significant decrease has occurred when the coupling for a class pair changes a) from fourth to first or second quartile or d) from third to first quartile. So, the variable $Increase\_L_{i,\,j\text{-}k,\,t}$ takes on a value of 1 if a significant increase has taken place in the coupling between a pair of elements, j and k for firm i at year t. Similarly, the variable $Decrease\_L_{i,\,j\text{-}k,\,t}$ takes on a value of 1 if a significant decrease has taken place.

As discussed before (Hypothesis 3a), successful patents by definition would receive a large number of citations. As many of these citing patents are likely to combine the same technology classes as the original patent, there may be a natural increase in the level of coupling between the classes combined in the original patent. To remove this effect, changes in coupling between elements were calculated after removing the descendants of patents in the first time period. It should be noted that the level of analysis for these hypotheses is at the level of technology class pairs. So changes in coupling are measured for pairs of classes that are combined in a patent. The change in structure is measured at the level of a firm as discussed next.

Extent of change in structure ($\text{Change}_{\text{i, t-3 to t-1, t}}$)

For calculating change, I compared the coupling matrix at time t ($\mathbf{L}_{\text{i, t-3 to t-1}}$), with the coupling matrix at time $t+3$ ($\mathbf{L}_{\text{i, t to t+2}}$) . This ensured that there are no common patents between the two coupling matrices that are being compared. *Change in structure* was measured as the weighted number of technology class pairs that had a significant change in coupling between two time periods. The weight is equal to

$\frac{p_i + p_j}{2} + \frac{p_i^{'} + p_j^{'}}{2}$ where p_i (p_j) and $p_i^{'}$ $(p_j^{'})$ represent the percentage of patents that belong to a technology class i (j) at time t and $t+3$ respectively. This ensures that change in coupling between two technology classes that contain a higher proportion of patents at either t or $t+3$ or both is given a larger weight. I logged this variable as it can take on only positive values.

Control Variables

The control variables that were included in the analysis are listed below.

Firm Size$_{i,\,t\text{-}1}$ The number of firm employees is used as a measure of firm size. This variable would control for the effects of scale and scope on technology search (Henderson and Cockburn, 1996). It would also control for inertia in large firms that may make a knowledge base rigid. Size data was obtained from Compustat, Japan Company Handbooks and Worldscope.

R&D Intensity$_{i,\ t-1}$ The firm's R&D intensity is a measure of the inputs to the technology search process. Firms that invest more in R&D generate more inventions and hence it is necessary to control for this input measure. R&D intensity is measured as R&D expenditure divided by net sales. This data was obtained from Compustat and Worldscope.

Product Diversification$_{i,\ t-1}$ Both positive and negative effects of diversification on the search process have been discussed in previous literature. Product diversification can have a positive effect as it increases the opportunities for using knowledge internally (Kamien and Schwartz, 1982). It may also have a negative effect because the top management team in a diversified firm may have a poor understanding of R&D and therefore is less likely to invest in R&D (Hoskisson and Hitt, 1988). Product diversification may also affect the rigidity of the knowledge base because of bureaucracy effects. It is measured as a dummy variable with a value of 1 if a firm had businesses other than semiconductors. I also used an alternative measure for product diversification. I used an entropy measure = $\Sigma\ P_j \times \ln (1/P_j)$, where P_j is defined as the percentage of firm sales in segment j and $\ln (1/P_j)$ is the weight for each segment j (Palepu, 1985). Segment sales information was collected from Compustat and Japan Company Handbook. Lack of segment wise data resulted in a reduced sample size when this measure was used.

Firm Performance$_{i,\, t\text{-}1}$ Again, both positive and negative effects of firm performance have been hypothesized previously. While profitable firms may have the slack to pursue exploration, they may have fewer incentives as compared to less profitable firms. Similarly, firm performance may affect the malleability of a knowledge base in both positive and negative ways. Firm performance data was obtained from Compustat, Japan Company Handbooks and Worldscope.

Non-American firm This variable controls for differences in research productivity and patenting propensity across different countries. This variable is a coded as a dummy variable and coded 1 if a firm is located outside North America and 0 if it is located in North America.

Technology Control$_{i,\, t\text{-}1}$ Citation frequency varies across classes independent of the usefulness of the invention. This variance may be due to factors such as patenting propensity and technological opportunity, which may vary across technological fields. So, a firm that patents mainly in classes that have high citation rates can get spuriously high citation rates for its inventions. To control for this effect, a technology control variable is defined. For each technology class, the average citation rate of all patents in a given year in that technology class is calculated. For each firm and each year, the technology control variable is defined as citation rate for each class in that year × number of the firm's inventions in that year that belong to that technology class.

Calendar Year Year dummies are included to control for any industry wide time varying effects as well as any trends in patenting rates and citation rates.

Technology Class Dummies are included to control for differences between firms in terms of the distribution of their patents across the semiconductor technology classes. Each class dummy was coded as 1 if the firm had a patent in that technology class in that year and 0 otherwise. Technology class dummies were not included in those models that included the *technology control* variable.

5.3 Research Design

While the sample data is from 1981 to 1999, hypotheses are tested for the years 1984 to 1999. Patents from 1995 to 1999 are excluded because there is not sufficient time available to observe the citations received by these patents. Patents from 1981 to 1983 were excluded because the patent portfolio is assumed to consist of patents from the previous three years.

Since the dependent variable in Hypothesis 1 , $Percent\_Exploratory_{i,\,t}$, is expressed as a percentage and thus restricted to the range (0,1), it is transformed with the logit transformation:

$$Logit\ (y) = ln\ \{y/(1-y)\}$$

The equation for Hypothesis 1 is given as:

$$Logit\ (Percent\_Exploratory_{i,\,t}) = \beta_0 + \beta_1\ Integration_{i,\,t\text{-}1\ to\ t\text{-}3} + \beta_2\ Integration_{i,\,t\text{-}1\ to\ t\text{-}3}^{\ 2} + \beta_3\ Number\ of\ Patents_{i,\,t\text{-}1} + \beta_4\ Firm\ Size_{i,\,t\text{-}1} + \beta_5\ R\&D\ Intensity_{i,\,t\text{-}1} + \beta_6\ Product\ Diversification_{i,\,t\text{-}1} + \beta_7\ Firm\ Performance_{i,\,t\text{-}1} + \beta_8\ Non\text{-}American\ Firm_i + Year\ dummies + Class\ dummies + Firm\ dummies + \varepsilon_{i,\,t\text{-}1}$$

For Hypothesis 2, where the dependent variable is a count measure, a fixed effects negative binomial models was used. Count models such as the Poisson model are necessary when the dependent variable takes on only positive and integer values. The negative binomial model which is a modified version of the Poisson model is more appropriate in this study due to the over-dispersion (i.e. variance exceeds the mean) in the data. The equation for hypothesis 2 is given as follows:

$$Ln\ (Usefulness_{i,\ t}) = \beta_0 + \beta_1\ Integration_{i,\ t\text{-}1\ to\ t\text{-}3} + \beta_2\ Integration_{i,\ t\text{-}1\ to\ t\text{-}3}{}^2 + \beta_3\ Number\ of\ Patents_{i,\ t\text{-}1} + \beta_4\ Firm\ Size_{i,\ t\text{-}1} + \beta_5\ R\&D\ Intensity_{i,\ t\text{-}1} + \beta_6\ Product\ Diversification_{i,\ t\text{-}1} + \beta_7\ Firm\ Performance_{i,\ t\text{-}1} + \beta_8\ Technology\ Control_{i,\ t\text{-}1} + \beta_9\ Non\text{-}American\ Firm_i + Year\ dummies + \varepsilon_{i,\ t\text{-}1}$$

The equations for Hypotheses 3a and 3b are given as:

$$Increase\_L_{i,\ j\text{-}k,\ t} = \beta_0 + \beta_1\ Success\ of\ Exploratory\ Inventions_{i,\ j\text{-}k,\ t\text{-}3\ to\ t\text{-}1} + \beta_2\ Perc\_Science_{i,\ j\text{-}k,\ t\text{-}3\ to\ t\text{-}1} + Year\ dummies$$

$$Decrease\_L_{i,\ j\text{-}k,\ t} = \beta_0 + \beta_1\ Success\ of\ Exploratory\ Inventions_{i,\ j\text{-}k,\ t\text{-}3\ to\ t\text{-}1} + \beta_2\ Perc\_Science_{i,\ j\text{-}k,\ t\text{-}3\ to\ t\text{-}1} + Year\ dummies$$

Since the dependent variable takes on only values of 0 or 1, the above equation was estimated through a random effects logit regression with each firm class pair being considered as one group. Analysis of the data showed that most of groups had a fixed outcome across years. As a fixed effects regression model will leave out all such groups while estimating the coefficients, I used a random effects model.

The equation for Hypotheses 4a, 4b and 4c is given as:

$$Log\ (Change_{i,\ t\text{-}3\ to\ t\text{-}1,\ t}) = \beta_0 + \beta_1\ Integration_{i,\ t\text{-}1\ to\ t\text{-}3} + \beta_2\ Integration_{i,\ t\text{-}1\ to\ t\text{-}3}^{\ 2} + \beta_3\ Sci\_Usage_{i,\ t\text{-}3\ to\ t\text{-}1} + \beta_4\ Sci\_Usage_{i,\ t\text{-}3\ to\ t\text{-}1} \times Integration_{i,\ t\text{-}1\ to\ t\text{-}3} + \beta_5\ Sci\_Usage_{i,\ t\text{-}3\ to\ t\text{-}1} \times Integration_{i,\ t\text{-}1\ to\ t\text{-}3}^{\ 2} + \beta_6\ Firm\ Size_{i,\ t\text{-}1\ to\ t\text{-}3} + \beta_7\ R\&D\ Intensity_{i,\ t\text{-}1\ to\ t\text{-}3} + \beta_8\ Product\ Diversification_{i,\ t\text{-}1} + \beta_9\ Firm\ Performance_{i,\ t\text{-}1\ to\ t\text{-}3} + \beta_{10}\ Non\text{-}American\ Firm_i + Firm\ dummies + Class\ dummies + Year\ dummies + \varepsilon_{i,t\text{-}1}$$

Since the dependent variable in the above equation can take on only positive values, I logged the dependent variable.

6 RESULTS

In this chapter, I report results from data analysis and hypothesis testing. First, I look at the differences between firms in terms of the structure of their knowledge bases in an attempt to show that the couplings that exist in a knowledge base are not driven by technological imperatives (§6.1). Second, I discuss the findings related to the effect of near decomposability on exploratory search (§6.2). Third, I discuss the findings for the hypothesis related to the usefulness of inventions (§6.3). Fourth, I discuss the effect of use of scientific knowledge and near decomposability on the changes that occur in a knowledge base (§6.4). Key results are summarized in §6.5.

6.1 Differences in knowledge-base structures between firms

It can be argued that near decomposability in the structure of the coupling matrix is a consequence and a mirror of near decomposability in the structure in the underlying interdependencies. However, if firms in the semiconductor industry have different structures even when only their semiconductor patents are considered, then it implies that decomposability in coupling is not being driven by decomposability in interdependencies. To show that firms differ in how they structure their knowledge bases, I compared each firm's knowledge-base structure with that of the knowledge-base structure of the entire industry because any firm differences that exist will be reflected in differences between individual firms and the industry. Further, I show such differences in terms of couplings between technology classes. More specifically, I assume that a difference or a mismatch exists when a firm provides strong coupling between two technology classes while the coupling between these technology classes is weak at the industry level or vice versa.

Given that firms differ in the technology classes that they use in a significant manner, it follows that there will be many instances in which coupling between two technology classes provided by a firm will be zero while coupling at the industry level is nonzero and hence my assertion that firms differ will be trivially true. To make a more stringent claim, I consider only those technology class pairs for each firm for which the firm has a nonzero coupling. Difference between firm and industry is measured as the number of technology class pairs for which there is a match between firm and industry divided by the total number of nonzero couplings that exist in the firm's knowledge base. Results show that this measure is less than 0.7 for about 75% of the firms in the sample.

I performed a similar analysis by comparing the knowledge-base structures of all firms with the knowledge-base structure of a single firm (Intel). This comparison was performed only for those technology classes for which both the firm and Intel had non-zero couplings. Again, I found that the difference measure was less than 0.7 for about 70% of the firms in the sample. These findings suggest that firms do differ from each other in terms of how they couple technology classes and that coupling involves choices made by the firm and is not entirely driven by technological imperatives or interdependencies between elements.

6.2 Results on exploratory search

Table 8 provides descriptive statistics and correlations for all variables at the firm level of analysis. In this section, I test Hypothesis 1 which states that the level of exploration in a firm’s inventions is related to the integration between its clusters of knowledge in a curvilinear (inverted-U shaped) manner. Table 9 presents the results for this hypothesis. Model 1 in Table 9 presents the results for the control variables. Model 2 adds the variable integration between clusters and Model 3 adds the squared term. Model 3 indicates support for Hypothesis 1 that integration between clusters of a firm’s knowledge base has a curvilinear relationship with the level of exploration in a firm’s inventions. The estimated coefficients indicate that the maximum value is reached at a value (-6.08/(2*-10.43)=0.29) that is within the observed range of the variable (0 to 1). Among the control variables, the number of patents has a negative effect on level of exploration while the other control variables such as firm size, performance, research intensity and diversification have no significant effect. Year dummies are also not significant indicating that there is no discernible trend in the level of exploration across time.

To test the sensitivity of the results to the assumption that a patent for which the across-tie ratio is greater than 0.5 is exploratory, I tried two alternative specifications. In the first case, I consider a patent to be exploratory if the across-tie ratio is greater than 0.75 and in the second case if the across-tie ratio is greater than zero. Results presented in for these two cases in (Model 4 and Model 5 in Table 9) show that Hypothesis 1 is still supported.

As mentioned earlier, lack of data on firm size and performance reduced the size of the sample. I tested Hypothesis 1 for the entire sample of 115 firms while excluding firm size, performance and research intensity. Results are presented in Model 6. Model 7 in Table 9 provides the results for the case where the definition of semiconductor classes is more restrictive as compared to the main model. In this model, I considered patents belonging to only 12 technology classes while constructing the coupling matrix for each firm as compared to 30 technology classes in the main model. Model 8 presents the results when the alternative measure for integration between clusters discussed in §5 is used. Measurement of exploration is also changed accordingly. The results from all these models provide support for Hypothesis 1.

6.3 Results on usefulness of inventions

Table 10 presents the results of the hypothesis testing for the number of citations. Model 1 in Table 10 presents the results for the control variables. Model 2 adds the variable integration between clusters and Model 3 adds the squared term. Model 3 indicates support for Hypothesis 2 that integration between clusters of a firm's knowledge base has a curvilinear relationship with the number of citations received by a firm's patents. The estimated coefficients indicate that the maximum value is reached at a value (-1.66/(2*-5.72)=0.15) that is within the observed range of the variable (0 to 1).

Among the control variables, the number of patents and the technology control variable are significant predictors of the number of citations as expected. Further, firm size, firm performance, research intensity and product diversification also increase the number of citations received. In the early part of the time period (1986 and 1987), the year dummies are positive and significant which is consistent with the observation that the number of citations received by patents is increasing over time. This increase in citations is not present in the later part of the time period, which is also consistent with the decreased time period that these patents were available for citation.

I tested the sensitivity of the results in a number of ways. First, I tested Hypothesis 2 with alternative measures of citations received. Model 4 in Table 10 presents the results when the dependable variable is number of non-self citations. That is, this measure excludes all citations that a firm makes to its own patents. Results are again consistent with Hypothesis 2 in that the number of citations is curvilinearly related to the integration between clusters. Model 5 presents the results when the dependant variable is number of citations received within six years of the patent's grant date. The dependent variable in the main model (model 3 in Table 10) is the number of citations received in all the subsequent years. When citations in all subsequent years are counted, patents in earlier years get more citations as they are available for citation for a longer period. While the year dummies control for this effect in the main model, counting the citations received within a fixed duration is an alternative way to ensure comparability across years. In this model, year dummies are positive and significant and increase over time which is consistent with the observation that the number of citations received by patents is increasing over time. Results from Model 5 in Table 10 provide weak support for Hypothesis 1 as the coefficient for the linear term integration between clusters fails to reach significance by a small margin.

I tested Hypothesis 2 for the entire sample of 115 firms while excluding firm size, performance and research intensity (Model 6 in Table 10). Results still provide support for Hypothesis 2. I also tested Hypothesis 2 with an alternative measure of product diversification, the entropy measure of product diversification. As segment wise sales data was not available for all companies, there is a reduction in sample size. Model 7 in Table 10 shows that this alternative measure of product diversification does not alter the support for Hypothesis 2. Model 8 in Table 10 uses an alternative method to control for variation in citations received by patents that belong to different technology classes. Instead of using the *technology control* variable, I used dummies for the 30 technology classes. Each class dummy variable takes on a value of 1 if the firm has a patent belonging to that class and zero otherwise. As can be seen from Model 8 in Table 10, Hypothesis 2 is still supported. As the *technology control* variable partly controls for the effect of reduced number of years that are available for citation for patents in later years, its exclusion in model 8 results in significant and negative coefficients for year dummies for the years 1991 to 1994.

The main model (Model 3 in Table 10) excludes observations for which the number of patents in the patent portfolio is zero because without patents the main independent variable integration between clusters cannot be calculated. To test the sensitivity of the results to the exclusion of these observations, I tested Hypothesis 2 by including these observations and assigning a value to integration between clusters for those observations where size of patent portfolio is zero. I used three different values - 0, 1 and the mean value of integration between clusters for each firm[33]. Models 9, 10 and 11 in Table 10 present the results for these three cases respectively. All three models provide support for Hypothesis 2.

Model 12 in Table 10 provides the results for the case where the definition of semiconductor classes is more restrictive (12 technology classes) as compared to the main model. I also tested Hypothesis 2 with an alternative conceptualization for integration between clusters (Model 13 in Table 10) discussed in §5. Again, results are consistent with Hypothesis 2. Overall, the results from the main model and the models that test the sensitivity of the results provide support for Hypothesis 2.

6.4 Results on change in coupling and structure of a knowledge base

First, I will discuss change in coupling at the level of technology class pairs and then discuss change in structure at the level of the firm. Table 11 provides descriptive statistics and correlations for all variables at the technology class pair level of analysis.

[33] The mean value for each firm is the mean of integration between clusters for all years where the number of patents in the patent portfolio is greater than zero.

Table 12 presents the results for Hypothesis 3a and Hypothesis 3b which state that the change in coupling between two knowledge elements is related to the success of prior exploratory inventions and use of science in exploratory inventions that combine these two elements.

Model 1 and Model 2 present the results for increase and decrease in coupling between technology classes as a function of the average citation rate and average use of scientific knowledge of all patents that combine a technology class pair. These two models show that a high average citation rate is more likely to lead to increased coupling between technology classes and less likely to lead to decreases in coupling between technology classes thus providing support for Hypothesis 3a. Use of scientific knowledge among patents that cite a technology class pair has no effect on the increase in coupling but decreases the likelihood that coupling between technology classes will decrease in the next time period thus providing only partial support for Hypothesis 3b. Model 3 and Model 4 present the results for increase and decrease in coupling while excluding firm size, firm performance and research intensity. Conclusions remain the same. Model 5 presents the results when the alternative measures of integration between clusters and exploratory patent are used[34]. Again, a higher average citation rate is likely to result in an increase in coupling between technology classes. Model 6 and Model 7 present the

[34] In this alternative measure of integration, an exploratory tie exists between two classes when the coupling between the two is less than the median value of coupling. According to the definition that I used, a significant decrease can occur only when coupling in the first period is higher than the median value of coupling. Consequently, there are no cases where a significant decrease in coupling can take place and hence only the results for increase in coupling are presented.

results when all patents and not just exploratory patents are considered while calculating average citation rate and average use of scientific knowledge. Again, Hypothesis 3a finds support while Hypothesis 3b finds only partial support. In models 4 to 7, coupling between technology classes in the previous time period has a negative and significant effect on increase in coupling and a positive and significant effect on decrease in coupling. This shows the expected regression to the mean effect i.e. a high coupling is more likely to be followed by a lower coupling in the next time period and vice versa.

Next, I look at the changes that occur in coupling at the level of a firm, i.e. the changes that occur in the structure of a knowledge base. Table 13 presents the results for the change that occurs in the structure of a firm's knowledge base. Model 1 in Table 13 presents the base line case with control variables. Model 2 adds the variable integration between clusters and Model 3 adds the squared term. Model 3 indicates support to Hypothesis 4a that the extent of change that occurs in the structure of a firm's knowledge base is curvilinearly related to the integration between clusters. The estimated coefficients indicate that the peak is reached at a value of .31 (=- 1.4/ (2* - 2.84)), which is within the observed range of integration between clusters. Model 4 adds the term for use of scientific knowledge. Model 4 finds support for Hypothesis 4b that firms that use scientific knowledge are more likely to undergo change in the structure of their knowledge base. Model 5 adds the interaction term use of scientific knowledge × integration between clusters and Model 6 adds the interaction term use of scientific knowledge × integration between clusters squared. Results from Model 6 indicate no support for Hypothesis 4c that use of scientific knowledge has its maximum effect on change when integration is at an intermediate value. None of the control variables except for performance and research intensity had an effect on the extent of change. Since performance and research intensity are highly correlated, I ran separate regressions including only one of these two variables at a time. Results show that neither of these two variables had a significant effect on the extent of change indicating that the significant effects on change that were present in the main model may have been spurious and due to the high correlation that these two variables had with each other.

Model 7 in Table 13 presents the results for the entire sample of 115 firms while excluding firm size, performance and research intensity. Model 8 in Table 13 provides the results for the case where the definition of semiconductor classes is more restrictive as compared to the main model. Model 9 presents the results when the alternative measure for integration between clusters is used. Hypothesis 4a and Hypothesis 4b are supported in all these models. Hypothesis 4c on the interaction between use of scientific knowledge and integration between clusters was not supported in any of the models.

6.5 Summary of key results

The findings of the study are summarized in Table 14. This study finds evidence that firms that have an intermediate level of integration between knowledge clusters are more likely to achieve higher levels of exploration, generate more useful inventions, and undergo more changes in the structure of their knowledge bases as compared to firms that have either a low or a high level of integration between knowledge clusters. There is support for the hypothesis that firms change the coupling between technology classes by looking at the success of past exploratory inventions that cite these technology classes together. Since firms with an intermediate level of integration between clusters are more likely to generate exploratory inventions, this finding provides additional support to the claim that firms with an intermediate level of integration between clusters are more likely to undergo changes in the structure of their knowledge bases.

The hypotheses on the effects of cognitive search on changes in coupling and structure received either no support or partial support. One possible reason for this is that the measure used for identifying science based patents is based on non-patent citations. Since non-patent citations include citations to non-scientific sources, this measure is noisy and hence may have led to lack of significant results.

7 Conclusions and Future Research

7.1 Conclusions

This dissertation investigates the relationship between the structure of a knowledge base and the effectiveness of technology search. Structure of a knowledge base is an important determinant of the usefulness of inventions as it plays an important role in mitigating the effects of computational complexity associated with technological search. Specifically, it can be shown that a nearly decomposable structure leads to both exploitation and exploration and thus improves the search process on high dimensional landscapes. A nearly decomposable structure also increases malleability of a knowledge base by increasing the absorptive capacity of the firm.

Prior literature in the management area has applied the idea of near decomposability to interdependence (Ethiraj & Levinthal, 2003; Rivkin and Siggelkow, 2003). Here, I apply the idea of near decomposability to couplings that exist in the made world and remain agnostic about its existence in interdependencies that exist in the natural world. Since interdependencies are usually not known a priori, it may not be appropriate to assume that the underlying problem (i.e. the interdependencies between elements) has any structure.

I make several theoretical contributions in this study. First, I emphasize the difference between coupling and interdependence and establish them as distinct concepts.

Interdependence is what exists in nature and needs to be determined. Coupling involves decision making and has an important role in improving our knowledge about interdependencies including discovering new ones. One could possibly raise a few objections to this conceptual difference between coupling and interdependence. First, coupling could just be a reflection of interdependence and near decomposability in the coupling matrix could just be an outcome of near decomposability in the interdependence matrix. If coupling were entirely to be decided by interdependence between knowledge elements, then all firms in an industry should exhibit the same pattern of couplings. This study shows that within the context of the semiconductor industry, individual firms vary considerably in their decision to couple technologies and thus even with the same technological context the actual patterns of combinative structuring differs across firms.

Second, if interdependence is something that is given and a part of the natural world, then it follows that interdependence between elements cannot be modified. This goes against the recommendations made by numerous researchers both in the organizational literature as well as in the modularity literature that interdependence between elements needs to be modified according to the situation. For example, modularization is supposed to involve a reduction of interdependence between the elements of a product (Baldwin and Clark, 2000). However, I argue that modularization actually involves a change in the coupling between elements and any ostensible change in the interdependence between elements is actually an outcome of using a different set of elements. For example, the interdependence between the display unit and the rest of the computer in a laptop is higher as compared to the interdependence between the display unit and the rest of the computer in a desktop. Moving from a desktop to a laptop does not result in an increase in the interdependence between the display unit and the rest of the computer. It actually involves using a new element which then implies that there has been a change in the coupling between elements.

My second theoretical contribution is that I explicate the role of modularity in technology search. Buffering (Thompson, 1967) or sealing off one module from another is usually seen as useful outcome of modularization because such sealing off is thought to prevent the spread of problems (Weick, 1976). For example, in software design, modularity has been seen as very desirable because it reduces ripple effects. Similarly, modularization has been extolled in the product design literature due its ability to limit ripple effects (Baldwin & Clark, 2000). Other recent studies point out the dangers of excessive modularity which include loss of competitive advantage (Fleming and Sorenson, 2001a) and losses due to the non-utilization of synergistic potential (Schilling, 2000). In this study, I argue that choosing independent modules and avoiding ripple effects is not actually desirable in technology search. An intermediate level of integration between modules is necessary to initiate boundary spanning adaptive walks that lead to exploration. While complete modularity can lead to exploration within a module, it limits exploration across modules.

Third, I point out the role played by the structure of a firm's knowledge base in making the knowledge base malleable. It has been argued previously that firms are constrained to local search due to the cognitive limitations of managers and lack of absorptive capacity that is required for long jumps and such local search by firms can lead to inertia. In this study I argue that firms can engage in search in distant neighborhoods or exploration even through a series of local moves. In the absence of near decomposability, these local moves fail to take the firm away from its local peak. However, an intermediate level of integration between clusters ensures that local moves at the level of a cluster sometimes lead to adaptive walks that span cluster boundaries and thus lead to exploration. While making such exploratory moves, a firm improves its knowledge of interdependencies and thus is able to bring about changes in its knowledge base.

Fourth, this study shows knowledge of successes (an example of experiential search) and scientific knowledge (an example of cognitive search) have both direct and indirect effects on the search process. In addition to the direct effect of showing where peaks are located on the landscape, these two types of knowledge have an indirect effect on the search process through their impact on the structure of a knowledge base. These changes in structure guide the firm to new peaks on the landscape. The delayed effect of science on technological inventions (Vincenti, 1990) suggests that this indirect effect is likely to be the more important effect.

From an empirical standpoint, this study introduces new measures of coupling and integration between clusters. The measure used for coupling also captures the combinative aspects of a firm’s technical competencies. This study is also one of the few that test the results from the NK model in an empirical setting. From the managerial practice point of view, this study seeks to make explicit the desired structure of a knowledge base that maximizes the effectiveness of technology search.

7.2 Limitations and Future Research

This study has several limitations. The empirical setting is the semiconductor industry and the usual caveats of a single industry study apply here. Second, I use patents as a measure of a firm’s knowledge base. There are some aspects of a firm’s knowledge base that are not captured in its patent portfolio. However, patents are of considerable importance in the semiconductor industry and the most significant aspects of a firm's knowledge base should be captured by its patent portfolio in this setting. Third, I do not measure the coupling between a firm’s knowledge elements directly. I use recombinations as evidence that two elements are coupled. Couplings of knowledge elements that do not result in patentable inventions are not measured. Next, I look at the extensions to this study.

First, I will discuss the extensions to the simulation study discussed in §3. Then, I will discuss the extensions to the empirical hypotheses that examine the relationship between structure of a knowledge base and technology search. Finally, I will discuss the extensions of the concept of coupling to other organizational issues.

In further work on the effect of coupling on the search on an NK landscape, I intend to extend the simulation study in two ways. First, in the simulation study described in §3, cluster membership does not reflect the underlying pattern of interdependencies, especially when interactions are between randomly chosen nodes. Assignment of nodes to clusters that reflects the assumed underlying interaction structure can possibly improve the search process (Ethiraj and Levinthal, 2003). This would match the decomposition of the coupling matrix with the decomposition of the underlying interaction matrix.

In the empirical study, I consider the knowledge structure of the firm that pertains only to semiconductors. In further work, I will examine the knowledge structure of the firm as a whole and study how the knowledge structures of different business units in a firm interact with each other and the effects of such interaction on the search process. Also, it has been assumed in this study that all changes in the structure of a knowledge base are desirable. In further work, I will examine the performance effects of changes in structure.

In this study, I mainly focus on the integration *between* clusters and how it affects the process of technological search. I argue that an intermediate level of coupling between clusters leads to both exploitation and exploration. It would be interesting to look at how integration *within* a cluster affects technological search. Also, the issue of how integration within clusters interacts with integration between clusters need to be addressed in future research. Whether they are complements or substitutes or co-vary with each other needs to be determined as well.

In this study, I focus on the usefulness of inventions. It is also important to look at the uncertainty associated with inventions because an increase in uncertainty (even at the cost of lower average usefulness) increases the chances that a firm finishes at the top of a race (March, 1991). Finishing at the top is especially important in technology search because the benefits of an invention are often captured by the first firm that generates the invention.

The exploration that is considered in this study is limited to boundary spanning across internal clusters of knowledge. It is important to consider other types of exploration such as spanning firm boundaries and how such exploration affects the outcomes of the search process and changes in the coupling between elements.

In the simulation study and in the theory section leading to the empirical hypotheses, I assumed that clusters and cluster boundaries can be precisely identified. However, analysis of the data showed that such precise clusters are unlikely to exist in practice.

Consequently, the method I used for measuring integration between clusters allows for "fuzzy" clusters. It would be useful to modify the simulation and refine the theoretical arguments to account for fuzzy clusters.

Rivkin (2000) suggests that complexity of a system increases as the number of interdependencies increases. He argues that such complexity can create barriers to imitation. So, the conclusion that follows is that any firm trying to ward off competitors should increase the interdependencies in its strategy. On the other hand, Kauffman suggests that the most complex behaviors are observed at intermediate levels of interdependence, which places the system at the edge of chaos[35]. These two arguments can be reconciled when one distinguishes between interdependence and coupling. While high interdependence increases the complexity of the system (that exists in the natural world), a near decomposable coupling matrix (i.e. a combination of high and low couplings) increases the complexity of the artifact[36] (examples include products, strategies and knowledge bases) and hence increases the complexity of behavior. Since, it is artifacts that are imitated and not the system, it would be interesting to study the effect of near decomposability on imitation.

I also intend to extend the concept of coupling to other organizational issues such as organization design, firm scope and intermediation. While the arguments in this study

[35] Systems that have low K are in the ordered regime and systems that have high K are in the chaotic regime. Complex behavior is observed at the edge of chaos (Kauffman, 1993).
[36] The complexity of the artifact increases because near decomposability leads to good peaks and increases the evolvability of the artifact.

have been directed at technological search, the mechanism through which coupling works can be extended to the above issues as well. For example, at the level of an economy, clusters of high coupling represent hierarchies and low couplings across clusters represent market interactions. Such a view of firm organization is compatible with the view that hierarchies and markets are intermediate points on a continuum (Hennart, 1993) between pure hierarchy (perfect coupling within a cluster) and pure market (no coupling across clusters, i.e., complete modularization). I intend to show that the decisions on firm scope are guided by the attempt to improve the search process. To show that such a view of firm scope can potentially improve upon the current explanations of firm scope, I intend to examine the effect of Information Technology on firm scope. Similarly, I intend to examine the effects of Information technology on organization design and intermediation to establish the usefulness of the concept of coupling for such issues.

Table 1
Knowledge Elements – Coffee Mug

Design or Knowledge Element	**Mug 1**	**Mug 2**
Material	Ceramic	Plastic
Tolerance	0.5 cm	<0.1 cm
Mfr. Process	Shape/glaze/bake	Injection mold
Height	9.5cm	16cm
Vessel Diameter	8	8.1
Width of Walls	0.3cm	0.1cm
Type of Walls	Single	Double
Weight	xx oz	yy oz
Handle Material	Ceramic	Plastic
Handle Shape	Complex	Complex
Handle Attachment	Integral	Glued on
Cap/ No Cap	No cap	Cap

Source: Baldwin & Clark, 2000: 26

Table 2
Interdependence Matrix - Coffee Mug

Design or Knowledge Element		1	2	3	4	5	6	7	8	9	10
Material	1	•	x	x			x	x	x		x
Tolerance	2	x	•	x			x	x	x	x	x
Mfr. Process	3	x	x	•			x	x	x	x	x
Height	4			x	•	x			x		x
Vessel Diameter	5		x	x	x	•	x	x	x		
Width of Walls	6	x	x	x	x	x	•	x	x		
Type of Walls	7	x	x	x		x	x	•	x	x	
Weight	8	x		x	x	x	x	x	•	x	
Handle Material	9	x	x	x				x	x	•	x
Handle Shape	10	x	x	x	x					x	•

Source: Baldwin and Clark, 2000: 41
x – implies that row parameter is dependent on the column parameter

Table 3
Coupling Matrix – Coffee Mug

Design or Knowledge Element	**A1**	**A2**	**A3**	**B1**	**B2**	**B3**	**B4**	**C1**	**C2**	**C3**	
A1	H	H	H								
A2	H	H	H						L		Manufacturing
A3	H	H	H	L							
B1			L	H	H	H	H				
B2				H	H	H	H				Vessel
B3				H	H	H	H				
B4				H	H	H	H	L			
C1							L	H	H	H	
C2		L						H	H	H	Handle
C3								H	H	H	

H – High coupling within a cluster
L - Low coupling across clusters

Table 4
Interdependence vs. coupling

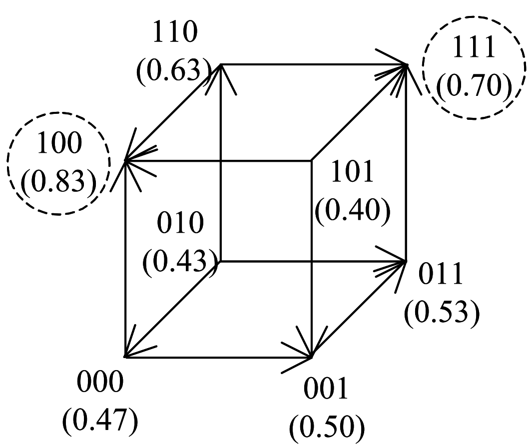
Interdependence	Coupling
Inherent relationship between elements ▪ Not known a priori ▪ May not be low	Decision taken on how the search across two interdependent elements should be combined
Exists in the natural world or the world of natural laws	Exists in the made world or the world of artifacts
Uncovering interdependencies and making valuable guesses on interdependencies is a key aspect of technological search	Mechanism for uncovering interdependencies
e.g., handle shape of the coffee mug is dependent on the width of the walls, height and diameter of the vessel	e.g., how closely tied is the design of the handle of the coffee mug to the design of the vessel

Table 5

Example of a N=3, K=2 landscape

Configuration of the System			**Value**			
State of Node 1	State of Node 2	State of Node 3	Value of Node 1	Value of Node 2	Value of Node 3	Total Value of the System
s_1	s_2	s_3	c_1	c_2	c_3	$C=\Sigma\, c_i / N$
0	0	0	.6	.3	.5	.47
0	0	1	.1	.5	.9	.50
0	1	0	.4	.8	.1	.43
0	1	1	.3	.5	.8	.53
1	0	0	.9	.9	.7	.83*
1	0	1	.7	.2	.3	.40
1	1	0	.6	.7	.6	.63
1	1	1	.7	.9	.5	.70*

* - Local peak



Arrows point in the direction of increasing values.

Table 6
Comparison of studies that have used the NK model

System	Studies	Nodes	Issues addressed
Organization	Levinthal (1997)	Sub-units within an organization	How does the coupling between the sub-units affect the survival of the organization?
Technology landscape	Kauffman et al (2000); Fleming and Sorenson, (2001a)	Technology recipes or components	Search on the technology landscape: local search vs. distant search; the effect of N and K on usefulness of inventions
Strategy	Rivkin (2000; 2001)	Components of a strategy	Effect of the number of interactions between the components (~ complexity of the strategy) on the imitatability and replicability of the strategy, when components can be copied, but less than perfectly.
Economy	Kauffman et al (1994), Levitan et al (1999)	Decisions or tasks or activities; A cluster of nodes represents a hierarchy	How should the decisions be coordinated? What is the optimal organization size?

Table 7
Summary of Hypotheses

Level of analysis: Firm

Hypothesis	**Independent variable**	**Dependent variable**	**Relationship**
Hypothesis 1	Integration between clusters, $Integration_{i,t\text{-}3\ to\ t\text{-}1}$	Percentage of exploratory inventions at time t, $Percent\_Exploratory_{i,t}$	Inverted U
Hypothesis 2	Integration between clusters, $Integration_{i,t\text{-}3\ to\ t\text{-}1}$	Usefulness of inventions at time t, $Usefulness_{i,t}$	Inverted U
Hypothesis 4a	Integration between clusters, $Integration_{i,t\text{-}3\ to\ t\text{-}1}$	Change in structure, $Change_{t\text{-}3\ to\ t\text{-}1,\ t}$	Inverted U
Hypothesis 4b	Use of scientific knowledge, $Sci\_Usage_{i,\ t\text{-}3\ to\ t\text{-}1}$	Change in structure, $Change_{t\text{-}3\ to\ t\text{-}1,\ t}$	Linear
Hypothesis 4c	Integration between clusters × Use of scientific knowledge, $Integration_{i,t\text{-}3\ to\ t\text{-}1} \times Sci\_Usage_{i,\ t\text{-}3\ to\ t\text{-}1}$	Change in structure, $Change_{t\text{-}3\ to\ t\text{-}1,\ t}$	Inverted U

Level of analysis: Technology class pairs

Hypothesis	**Independent variable**	**Dependent variable**	**Relationship**
Hypothesis 3a	Success of exploratory patents that combine classes j and k, $Success\_Exploratory_{i,\ j\text{-}k,\ t\text{-}3\ to\ t\text{-}1}$	Increase/ Decrease in the coupling between classes j and k, $Increase\_L_{i,\ j\text{-}k,\ t}$, $Decrease\_L_{i,\ j\text{-}k,\ t}$	Linear
Hypothesis 3b	Percentage of exploratory patents that combine classes j and k, $Perc\_Science_{i,\ j\text{-}k,\ t\text{-}3\ to\ t\text{-}1}$	Increase/ Decrease in the coupling between classes j and k, $Increase\_L_{i,\ j\text{-}k,\ t}$, $Decrease\_L_{i,\ j\text{-}k,\ t}$	Linear

TABLE 8
Descriptive Statistics and Correlations for Firm Level of Analysis [a,b]

	Variable	Mean	s.d.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12
1.	Number of citations	684.19	1242.33	0	7633												
2.	Number of patents	85.71	155.88	0	1042	0.88*											
3.	Number of patents in patent portfolio	202.16	369.01	1	2206	0.85*	0.97*										
4.	Integration between clusters	0.16	0.16	0	1	-0.30*	-0.31*	-0.31*									
5.	Reliance on science	0.41	0.24	0	1	0.08*	0.07	0.08*	-0.06								
6.	Technology control	671.92	1189.04	0	6569	0.97*	0.93*	0.90*	-0.31*	0.07							
7.	Research intensity	0.14	0.47	0	7.97	-0.06	-0.06	-0.06	0.05	0.05	-0.06						
8.	Firm size	43716.82	90016.44	22	593000	0.58*	0.51*	0.56*	-0.26*	0.13*	0.58*	-0.07					
9.	Firm performance	-0.07	0.94	-15.5	0.33	0.06	0.06	0.05	-0.02	-0.01	0.06	-0.97*	0.05				
10.	Product diversification	-15.52	0.50	0	1	0.24*	0.33*	0.34*	-0.17*	-0.12*	0.33*	-0.15*	0.27*	0.09*			
11.	Non-American firm	0.27	0.44	0	1	0.21*	0.33*	0.34*	-0.08	-0.13*	0.33*	-0.10*	0.16*	0.06	0.67*		
12.	Level of exploration	0.16	0.17	0	1	-0.14*	-0.14*	-0.14*	0.12*	0.02	-0.13*	-0.03	-0.04	0.03	-1e-3	-0.01	
13.	Change in structure	24.43	21.48	0	179.2	0.27*	0.28*	0.27*	-0.30*	0.12*	0.24*	-0.07	0.22*	0.09*	0.06	-0.05	-0.08

[a] n=639 firm years

[b] All independent variables except for number of patents are lagged by one year

[*] $p<.05$

TABLE 9
Results of Fixed Effects Analyses for Level of Exploration

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	-2.52 ***	-2.69 ***	-3.02 ***	-4.37 ***	-2.05***
	0.45	0.46	0.46	0.60	0.38
Integration between clusters		0.94 †	6.28 ***	7.21 ***	4.01**
		0.55	1.54	2.01	1.27
Integration between clusters squared			-10.77 ***	-9.89 *	-7.05**
			2.91	3.80	2.41
Number of patents	-2.70E-03 **	-2.67E-03 **	-2.33E-03 **	-2.64E-03 *	-1.40E-03*
	8.02E-04	8.00E-04	7.94E-04	1.04E-03	6.57E-04
Research Intensity	-1.50E-03	-0.02	0.07	0.49	-2.02*
	1.05	1.05	1.04	1.35	0.86
Firm size	1.16E-06	1.14E-06	1.14E-06	-1.28E-07	1.19E-06
	2.87E-06	2.86E-06	2.82E-06	3.68E-06	2.33E-06
Firm performance	-3.85E-03	-0.03	0.06	0.20	-0.95*
	0.47	0.47	0.47	0.61	0.39
Product diversification	-0.31	-0.35	-0.43	-0.53	-0.43
	0.36	0.36	0.36	0.47	0.30
1985	-0.11	-0.10	-0.08	0.03	-0.07
	0.31	0.31	0.30	0.39	0.25
1986	-0.17	-0.16	-0.10	-0.11	-0.12
	0.30	0.30	0.30	0.39	0.25

1987	-0.47	-0.45	-0.34	-0.28	-0.22
	0.30	0.30	0.30	0.39	0.25
1988	-0.01	0.02	0.04	0.01	0.08
	0.30	0.30	0.30	0.39	0.25
1989	-0.05	-0.03	-0.03	-0.31	0.06
	0.30	0.30	0.30	0.39	0.25
1990	-0.10	-0.08	-0.07	-0.09	-4.90E-03
	0.31	0.31	0.30	0.39	0.25
1991	-0.27	-0.23	-0.20	-0.34	-0.10
	0.31	0.31	0.30	0.39	0.25
1992	0.14	0.17	0.24	0.24	0.28
	0.31	0.31	0.30	0.39	0.25
1993	0.36	0.37	0.40	0.18	0.40
	0.31	0.31	0.30	0.40	0.25
1994	0.26	0.29	0.33	0.31	0.49†
	0.32	0.32	0.32	0.41	0.26
Number of observations	568	568	568	568	568
Number of groups	85	85	85	85	85

[a] All regressions include class dummies for which results have not been displayed.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

TABLE 9 (CONTINUED)
Results of Fixed Effects Analyses for Level of Exploration

Variable	Model 6	Model 7	Model 8
Constant	-4.17 ***	-5.91 ***	-2.54 ***
	0.34	0.90	0.42
Integration between clusters	5.37 ***	7.82 ***	3.66 ***
	1.02	2.05	1.01
Integration between clusters squared	-7.92 ***	-8.57 **	-4.18 **
	1.60	3.17	1.34
Number of patents	-2.61E-03 **	-0.01 **	-1.56E-03 *
	7.93E-04	2.57E-03	6.51E-04
Research Intensity		1.77	-1.39
		1.96	0.86
Firm size		-1.10E-05 *	8.22E-07
		5.23E-06	2.32E-06
Firm performance		0.84	-0.68 †
		0.88	0.39
Product diversification	0.01	-1.95 **	-0.38
	0.26	0.71	0.29
1985	0.11	-0.69	-0.02
	0.28	0.60	0.25
1986	0.13	-0.57	-0.14
	0.27	0.60	0.25
1987	-0.12	-0.60	-0.20

	0.27	0.60	0.25
1988	0.32	-0.90	-0.01
	0.26	0.60	0.25
1989	0.34	-0.84	-0.03
	0.26	0.60	0.25
1990	0.18	-1.61 **	-0.05
	0.27	0.60	0.25
1991	-0.02	-1.16 †	-0.11
	0.27	0.60	0.25
1992	0.44	-0.94	0.19
	0.27	0.60	0.25
1993	0.48 †	-0.75	0.26
	0.27	0.60	0.25
1994	0.53 †	-0.72	0.27
	0.29	0.64	0.26
Number of observations	759	501	568
Number of groups	115	75	85

[a] All regressions include class dummies for which results have not been displayed.

† $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

TABLE 10
Results of Fixed Effects Negative Binomial Regression Analyses for Number of Citations

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	-0.04	0.24	0.07	0.21	0.07	0.15	0.05
	0.15	0.15	0.16	0.16	0.16	0.14	0.17
Integration between clusters		-1.11***	1.66*	1.76*	1.10	1.60**	1.74*
		0.26	0.75	0.76	0.75	0.58	0.76
Integration between clusters squared			-5.72***	-5.83***	-5.00**	-3.96***	-5.73***
			1.54	1.56	1.51	1.05	1.54
Number of patents	6.74E-04*	6.44E-04*	7.12E-04*	7.30E-04*	1.05E-03***	4.02E-04	6.87E-04*
	2.92E-04	2.84E-04	2.82E-04	2.83E-04	2.49E-04	3.11E-04	2.77E-04
Research Intensity	1.61**	1.58**	1.56**	1.59**	1.14**		1.68**
	0.50	0.48	0.47	0.47	0.43		0.49
Firm size	3.29E-06***	3.07E-06***	3.06E-06***	3.04E-06***	2.87E-06***		3.02E-06***
	4.34E-07	4.29E-07	4.34E-07	4.34E-07	4.47E-07		5.05E-07
Firm performance	0.70**	0.69**	0.69**	0.71**	0.50*		0.75**
	0.23	0.22	0.22	0.22	0.20		0.23
Product diversification	0.41**	0.39**	0.33**	0.32**	0.39**	0.54***	0.67***
	0.12	0.12	0.12	0.12	0.11	0.09	0.12
Non-American	0.37*	0.33†	0.35†	0.30†	0.31†	-0.43***	0.00
	0.18	0.18	0.18	0.18	0.18	0.10	0.19
Technology control	3.30E-04***	3.26E-04***	3.30E-04***	3.32E-04***	2.95E-04***	4.53E-04***	3.16E-04***
	4.52E-05	4.40E-05	4.39E-05	4.41E-05	3.97E-05	4.58E-05	4.43E-05
1985	0.13	0.12	0.12	0.13	0.16	-0.08	0.14
	0.12	0.12	0.12	0.12	0.13	0.13	0.12

1986	0.25*	0.25*	0.25*	0.26*	0.27*	0.12	0.23*
	0.12	0.11	0.11	0.11	0.13	0.12	0.11
1987	0.27*	0.25*	0.25*	0.25*	0.32*	0.16	0.25*
	0.12	0.11	0.11	0.11	0.13	0.12	0.11
1988	0.21†	0.18	0.18	0.18	0.32*	0.10	0.20†
	0.12	0.12	0.12	0.12	0.13	0.12	0.12
1989	0.18	0.16	0.16	0.16	0.42**	0.01	0.21†
	0.12	0.12	0.12	0.11	0.12	0.12	0.12
1990	0.07	0.04	0.04	0.05	0.44***	-0.16	0.10
	0.12	0.12	0.12	0.12	0.12	0.12	0.12
1991	0.07	0.02	0.03	0.03	0.54***	-0.12	0.09
	0.12	0.12	0.12	0.12	0.12	0.12	0.12
1992	0.01	-0.04	-0.03	-0.04	0.57***	-0.16	0.04
	0.12	0.12	0.12	0.12	0.12	0.12	0.12
1993	1.8e-03	-0.03	-4.5E-03	-0.02	0.61***	-0.09	0.06
	0.13	0.12	0.12	0.12	0.13	0.12	0.12
1994	-0.07	-0.11	-0.09	-0.10	0.48***	-0.20	-0.03
	0.14	0.13	0.13	0.13	0.14	0.13	0.13
Log Likelihood	-2932.91	-2923.49	-2914.4	-2854.33	-2714.93	-3873.87	-2835.58
Number of observations	617	617	617	617	617	847	604
Number of groups	85	85	85	85	85	115	81

† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

TABLE 10 (CONTINUED)
Results of Fixed Effects Negative Binomial Regression Analyses for Number of Citations

Variable	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Constant	-0.17	-0.95***	-0.33*	-0.77***	-0.57**	-0.38*
	0.15	0.15	0.15	0.17	0.18	0.19
Integration between clusters	1.15†	6.00***	1.62**	2.34**	2.82***	4.96***
	0.68	0.90	0.51	0.81	0.65	0.78
Integration between clusters squared	-3.67**	-11.64***	-3.58***	-5.28**	-5.03***	-7.07***
	1.35	2.02	0.57	1.58	1.07	1.07
Number of patents	1.74E-03***	6.08E-04†	6.93E-04*	3.96E-04	2.22E-03***	8.80E-04**
	1.15E-04	3.25E-04	3.01E-04	3.29E-04	5.38E-04	2.76E-04
Research Intensity	1.43**	1.87***	2.10***	2.03***	1.83**	1.89***
	0.42	0.43	0.47	0.42	0.57	0.47
Firm size	4.59E-07	3.84E-06***	3.48E-06***	3.80E-06***	3.63E-06***	2.92E-06***
	3.72E-07	4.61E-07	4.44E-07	4.53E-07	4.92E-07	4.29E-07
Firm performance	0.60**	0.83***	0.93***	0.89***	0.88**	0.83***
	0.20	0.20	0.22	0.20	0.28	0.22
Product diversification	-0.04	0.47***	0.47***	0.56***	0.34*	0.27*
	0.08	0.13	0.12	0.13	0.14	0.11
Non-American	0.26	0.43*	0.50**	0.43*	0.72**	0.32†
	0.18	0.18	0.18	0.18	0.21	0.18
Technology control	Class	3.78E-04***	3.48E-04***	3.84E-04***	4.62E-04***	2.99E-04***
	dummies	4.94E-05	4.62E-05	4.93E-05	7.83E-05	4.32E-05
1985	0.01	0.07	0.10	0.04	0.12	0.17
	0.07	0.14	0.13	0.14	0.14	0.12

1986	0.05	0.26*	0.24*	0.23†	0.31*	0.24*
	0.07	0.13	0.12	0.13	0.13	0.11
1987	0.08	0.26*	0.23†	0.24†	0.35**	0.27*
	0.07	0.13	0.12	0.13	0.13	0.11
1988	0.04	0.24†	0.18	0.22†	0.23†	0.20†
	0.07	0.13	0.12	0.13	0.13	0.11
1989	-0.01	0.17	0.11	0.16	0.20	0.15
	0.07	0.13	0.12	0.13	0.13	0.11
1990	-0.10	0.12	0.04	0.10	0.07	0.06
	0.07	0.13	0.12	0.13	0.13	0.11
1991	-0.17*	0.13	0.03	0.11	0.04	0.02
	0.07	0.13	0.12	0.13	0.14	0.11
1992	-0.40***	0.12	-4.9E-04	0.11	0.00	-0.05
	0.07	0.13	0.13	0.13	0.13	0.12
1993	-0.55***	0.13	-4.7E-03	0.11	-0.04	-0.04
	0.08	0.14	0.13	0.14	0.14	0.12
1994	-0.89***	0.08	-0.08	0.07	-0.20	-0.17
	0.08	0.15	0.14	0.15	0.15	0.13
Log Likelihood	-2705.5	-3134.99	-3101.99	-3156.67	-2463.53	-2906.73
Number of observations	617	739	739	739	561	617
Number of groups	85	89	89	89	74	85

† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

TABLE 11
Descriptive Statistics and Correlations for Technology class pair Level of Analysis [a]

	Variable	Mean	s.d.	Min.	Max.	1	2	3	4	5	6	7	8	9
1	Increase in coupling	0.05	0.21	0	1									
2	Decrease in coupling	0.03	0.16	0	1	-0.04*								
3	Average citation rate	5.91	7.13	0	136	0.03*	-0.05*							
4	Average use of scientific knowledge	0.46	0.48	0	1	-0.01	-0.04*	0.10*						
5	Number of patents that cite class pair in previous time period	1.20	0.59	1	11	0.02*	-0.03*	0.00	0.01					
6	Research Intensity	0.10	0.15	0	5.36	0.01*	-0.02*	0.06*	0.01	0.01				
7	Firm size	119889.10	141219.60	18.67	756193	-0.05*	-0.04*	-0.04*	0.07*	-0.03*	-0.13*			
8	Firm performance	0.02	0.29	-10.29	0.22	4.50E-03	2.70E-03	0.01	2.60E-03	1.00E-04	-0.95*	0.07*		
9	Product diversification	0.69	0.46	0	1	-0.05*	0.04*	-0.19*	-0.10*	4.90E-03	-0.18*	-0.08*	0.06*	
10	Non-American	0.46	0.50	0	1	-0.04*	0.03*	-0.15*	-0.08*	0.03*	-0.05*	-0.02*	0.02*	0.61*

[a] *n*=26589 technology class pair years
[*] $p<.05$

TABLE 12
Results of Random Effects Regression Analyses for Change in Coupling between Technology Class Pairs[a]

Variable	Model 1 Increase in coupling	Model 2 Decrease in coupling	Model 3 Increase in coupling	Model 4 Decrease in coupling	Model 5 Increase in coupling	Model 6 Increase in coupling	Model 7 Decrease in coupling
Constant	-5.09***	-7.32***	-5.05***	-11.22***	-4.63***	-5.24***	1.97***
	0.33	0.72	0.24	0.60	0.17	0.15	0.10
Average of citations received	0.02**	-0.11***	0.03***	-0.16***	0.02***	0.02***	-0.04***
	0.01	0.02	0.01	0.02	3.04E-03	2.65 E-03	2.54 E-03
Average use of scientific knowledge	-0.16	-0.73**	-0.14	-0.53*	-0.02	-4.95E-03	-0.09*
	0.10	0.26	0.09	0.22	0.05	0.04	0.03
Coupling between class pair in previous time period	-0.11	0.24	-0.02	0.40**	-0.22***	-0.64***	0.03***
	0.07	0.15	0.07	0.15	0.03	0.02	0.00
Across cluster tie						0.31***	-5.96***
						0.05	0.09
Research Intensity	2.98**	-25.47***			3.11***	4.83***	-8.93***
	1.05	4.13			0.63	0.54	0.53
Firm size	-2.48E-06***	-8.49E-06***			-5.66E-07**	4.31E-07*	-3.61E-06***
	4.23E-07	1.41E-06			2.01E-07	1.74E-07	1.66E-07
Firm performance	1.56**	-7.06***			1.67***	2.53***	-4.34***
	0.52	1.27			0.33	0.29	0.27
Product diversification	-0.41**	-0.77†	-0.68***	0.19	-0.27***	-0.19**	-0.05
	0.15	0.42	0.10	0.25	0.08	0.07	0.06
Non-American	-0.15	1.02**	0.08	0.78**	-0.08	-0.02	-0.51***
	0.14	0.38	0.10	0.24	0.07	0.06	0.06

1985	0.25	-0.29	0.26	-0.33	0.16	0.10	-0.05
	0.23	0.44	0.19	0.39	0.12	0.11	0.07
1986	0.35	-0.12	0.36†	-0.23	0.35**	0.26*	-0.31***
	0.23	0.45	0.19	0.40	0.12	0.11	0.07
1987	0.10	-0.31	0.13	-0.56	0.28*	0.23*	-0.44***
	0.24	0.45	0.20	0.41	0.12	0.11	0.07
1988	0.25	-0.24	0.44*	-0.45	0.46***	0.37**	-0.59***
	0.23	0.46	0.19	0.40	0.12	0.11	0.07
1989	-0.43†	-1.21*	-0.30	-1.38**	0.28*	0.26*	-0.56***
	0.24	0.48	0.20	0.42	0.12	0.11	0.06
1990	-0.19	-1.36**	-0.04	-1.37**	0.24*	0.23*	-0.53***
	0.23	0.47	0.19	0.42	0.12	0.11	0.06
1991	-0.24	-1.42**	-0.08	-1.45**	0.39**	0.35**	-0.57***
	0.23	0.48	0.19	0.42	0.12	0.11	0.06
1992	0.27	-1.67***	0.41*	-1.72***	0.93***	0.84***	-0.88***
	0.22	0.47	0.18	0.41	0.12	0.11	0.06
1993	0.62**	-1.81***	0.66***	-1.74***	1.27***	1.18***	-1.11***
	0.22	0.47	0.18	0.41	0.12	0.10	0.06
Number of observations	26589	26589	29789	29789	67796	135500	135500
Number of groups	12648	12648	14076	14076	22173	36734	36734
Log Likelihood	-4590.21	-2213.76	-5426.38	-2560.46	-15759.64	-18770.52	-55376.76

[a] All regressions include dummies for each firm class pair for which results have not been displayed.

† $p<.10$

* $p<.05$

** $p<.01$

*** $p<.001$

TABLE 13
Results of Fixed Effects Regression Analyses for Change in Structure[a]

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	2.45 ***	2.49 ***	2.34 ***	2.16 ***	2.16 ***	2.14 ***
	0.32	0.32	0.32	0.32	0.32	0.32
Integration between clusters		-0.22	1.41 **	1.19 *	1.17 *	1.21 *
		0.21	0.52	0.52	0.55	0.56
Integration between clusters squared			-2.84 **	-2.46 **	-2.44 **	-2.54 **
			0.84	0.84	0.88	0.92
Use of scientific knowledge				0.50 **	0.50 **	0.54 **
				0.17	0.17	0.19
Integration between clusters × Use of scientific knowledge					0.08	0.35
					0.73	0.98
Integration between clusters squared × Use of scientific knowledge						-1.44
						3.44
Number of patents in patent portfolio	-1.27E-04	-1.33E-04	-7.41E-05	-1.05E-04	-1.05E-04	-1.01E-04
	1.63E-04	1.63E-04	1.62E-04	1.60E-04	1.61E-04	1.61E-04
Research Intensity	-2.61 **	-2.63 **	-2.56 **	-2.78 **	-2.77 **	-2.77 **
	0.97	0.97	0.96	0.95	0.95	0.96
Firm size	1.45E-08	1.33E-08	-1.57E-08	-9.63E-09	-7.57E-09	-1.33E-08
	8.40E-07	8.40E-07	8.29E-07	8.21E-07	8.22E-07	8.23E-07
Firm performance	-1.15 **	-1.16 **	-1.14 **	-1.25 **	-1.25 **	-1.25 **
	0.43	0.43	0.42	0.42	0.42	0.42
Product diversification	0.08	0.08	0.06	0.11	0.11	0.11
	0.17	0.17	0.17	0.16	0.17	0.17

Non-American	0.31	0.33	0.44	0.41	0.41	0.42
	0.79	0.79	0.78	0.77	0.77	0.78
1985	0.16	0.16	0.15	0.15	0.15	0.15
	0.12	0.12	0.11	0.11	0.11	0.11
1986	0.23 *	0.23 *	0.25 *	0.25 *	0.25 *	0.24 *
	0.11	0.11	0.11	0.11	0.11	0.11
1987	0.22 †	0.21 †	0.23 *	0.22 †	0.22 †	0.22 †
	0.12	0.12	0.11	0.11	0.11	0.11
1988	0.32 **	0.31 **	0.31 **	0.31 **	0.31 **	0.31 **
	0.12	0.12	0.11	0.11	0.11	0.11
1989	0.28 *	0.27 *	0.26 *	0.25 *	0.25 *	0.25 *
	0.12	0.12	0.11	0.11	0.11	0.11
1990	0.40 **	0.39 **	0.38 **	0.37 **	0.37 **	0.36 **
	0.12	0.12	0.12	0.12	0.12	0.12
1991	0.41 **	0.40 **	0.39 **	0.38 **	0.38 **	0.38 **
	0.12	0.12	0.12	0.12	0.12	0.12
1992	0.55 ***	0.54 ***	0.54 ***	0.53 ***	0.53 ***	0.53 ***
	0.12	0.12	0.12	0.12	0.12	0.12
1993	0.60 ***	0.59 ***	0.59 ***	0.61 ***	0.61 ***	0.60 ***
	0.12	0.12	0.12	0.12	0.12	0.12
Number of observations	527	527	527	527	527	527
Number of groups	85	85	85	85	85	85

[a] All regressions include class dummies for which results have not been displayed.

† $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

TABLE 13 (CONTINUED)
Results of Fixed Effects Regression Analyses for Change in Structure[a]

	Model 7	Model 8	Model 9
Constant	2.06 ***	2.03 ***	1.06 †
	0.14	0.39	0.61
Integration between clusters	1.04 *	1.77 **	2.14 ***
	0.44	0.53	0.50
Integration between clusters squared	-2.51 ***	-2.72 ***	-3.11 ***
	0.68	0.74	0.66
Use of scientific knowledge	0.39 *	0.57 **	1.02 ***
	0.16	0.20	0.24
Integration between clusters × Use of scientific knowledge	-0.69	-0.76	0.26
	0.73	1.00	0.50
Integration between clusters squared × Use of scientific knowledge	1.72	-0.08	-6.19 **
	2.01	2.11	2.18
Number of patents in patent portfolio	-3.15E-04 *	-3.05E-05	-1.21E-04
	1.56E-04	3.37E-04	1.52E-04
Research Intensity		-2.06 †	-2.21 *
		1.20	0.94
Firm size		5.16E-07	0.09
		9.80E-07	0.06
Firm performance		-0.93 †	-0.96 *
		0.53	0.42
Product diversification	-0.01	0.05	0.16
	0.12	0.20	0.16

Non-American	-0.07	-0.06	0.32
	0.12	0.95	0.75
1985	3.93E-03	0.16	0.20 †
	0.11	0.14	0.11
1986	0.16	0.19	0.20 †
	0.10	0.14	0.11
1987	0.17	0.20	0.21 †
	0.10	0.14	0.11
1988	0.21 *	0.20	0.30 **
	0.10	0.14	0.11
1989	0.17 †	0.21	0.22 *
	0.10	0.14	0.11
1990	0.27 **	0.29 *	0.33 **
	0.10	0.14	0.11
1991	0.35 **	0.36 *	0.34 **
	0.10	0.14	0.11
1992	0.48 ***	0.48 **	0.47 ***
	0.11	0.15	0.11
1993	0.64 ***	0.69 ***	0.54 ***
	0.11	0.15	0.12
Number of observations	719	482	527
Number of groups	115	75	85

[a] All regressions include class dummies for which results have not been displayed.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

Table 14
Proposed effects and findings

Hypothesis	Independent variable	Dependent variable	Relationship	Findings
H1	Integration between clusters	Percentage of exploratory inventions at time t	Inverted U	Inverted U
H2	Integration between clusters	Usefulness of inventions at time t	Inverted U	Inverted U
H3a	Success of exploratory patents that combine classes j and k	Increase/ Decrease in the coupling between classes j and k	Linear	Linear
H3b	Percentage of exploratory patents that combine classes j and k and cite a non-patent reference	Increase/ Decrease in the coupling between classes j and k	Linear	Not significant
H4a	Integration between clusters	Change in structure	Inverted U	Inverted U
H4b	Use of scientific knowledge	Change in structure	Linear	Linear
H4c	Integration between clusters × Use of scientific knowledge	Change in structure	Inverted U	Not significant

Figure 1
Determinants of Effectiveness of Technological Search

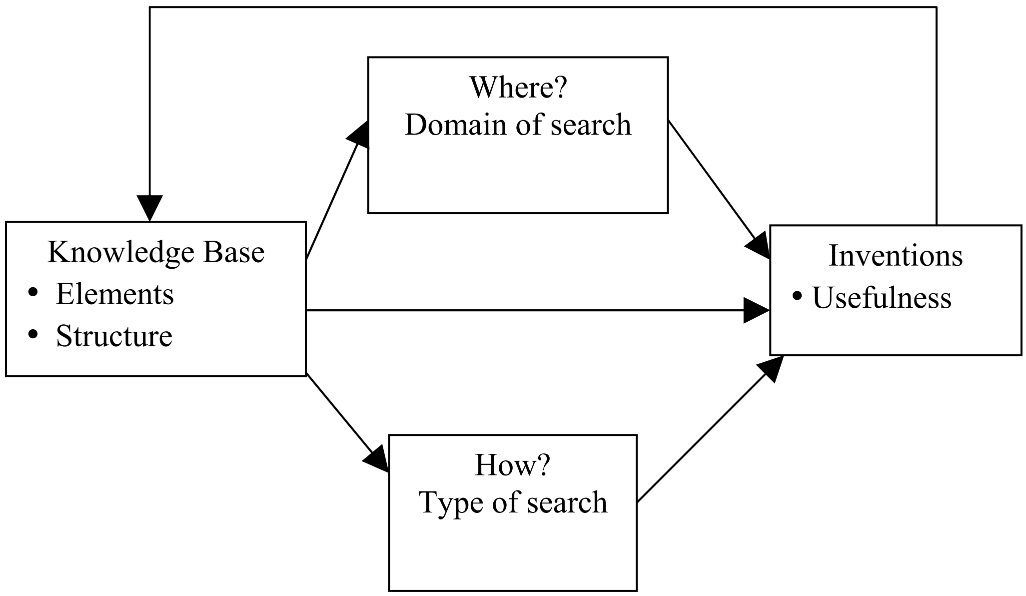


Figure 2
Near decomposability in a matrix

	A1	**A2**	**A3**	**B1**	**B2**	**B3**	**B4**	**C1**	**C2**	**C3**
A1	X	X	X							
A2	X	X	X							
A3	X	X	X	X						
B1			X	X	X	X	X			
B2				X	X	X	X			
B3				X	X	X	X			
B4				X	X	X	X	X		
C1							X	X	X	X
C2								X	X	X
C3								X	X	X

X – interaction exists between row and column elements

Figure 3
Interdependence and coupling

a) Interaction matrix for two-way interdependencies (K=2)

	A1	A2	A3	B1	B2	B3	B4	C1	C2	C3
A1	X	X	X	X			X			X
A2	X	X				X		X		
A3	X	X	X	X					X	
B1		X	X	X	X	X	X			X
B2				X	X		X	X	X	
B3	X				X	X	X			
B4		X		X	X	X	X	X		
C1							X	X	X	X
C2		X		X				X	X	X
C3	X				X				X	X

X – Row and column elements are interdependent

b) Coupling matrix with near decomposability

	A1	A2	A3	B1	B2	B3	B4	C1	C2	C3
A1	H	H	H							
A2	H	H	H						L	
A3	H	H	H	L						
B1			L	H	H	H	H			
B2				H	H	H	H			
B3				H	H	H	H			
B4				H	H	H	H	L		
C1							L	H	H	H
C2		L						H	H	H
C3								H	H	H

H – High Coupling
L- Low Coupling

Figure 4
Broad alternatives for coupling (adapted from Kauffman (1995:255))

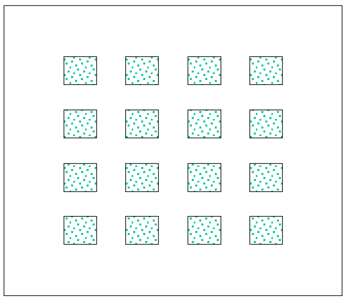
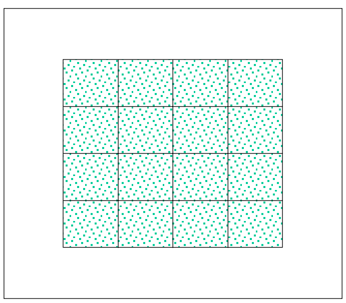
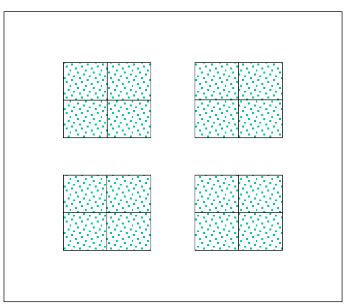
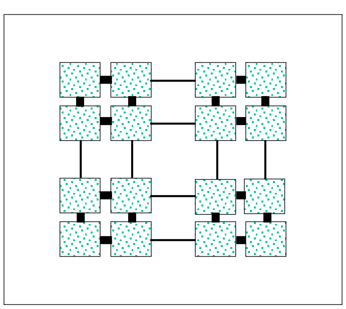
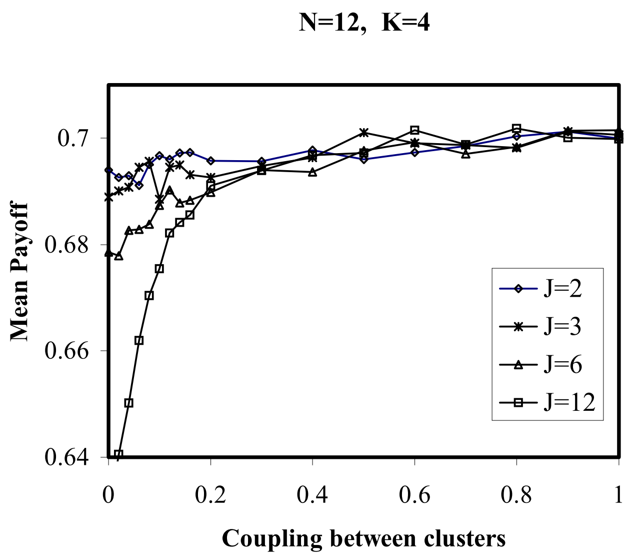
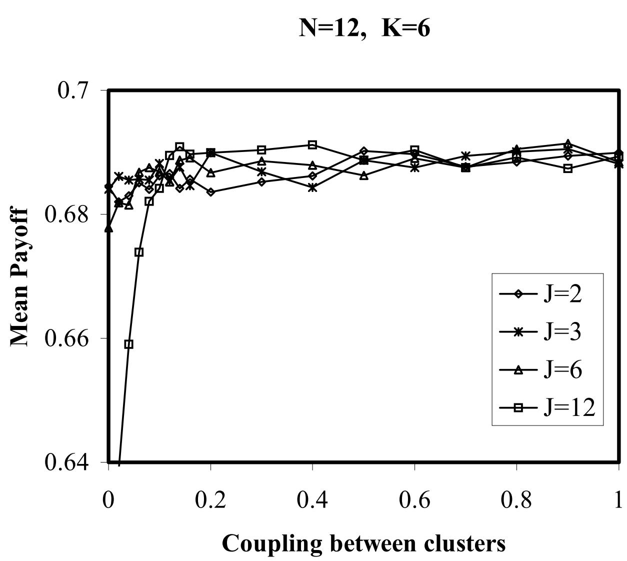
		Cluster size (N_J)	Number of clusters (J)	Coupling (L)	Interpretation
A		1	16	Zero between all the nodes	A perfectly decentralized system
B		16	1	Perfect between all the nodes	A perfectly centralized system
C		4	4	Perfect within cluster and zero between all nodes	A system that combines decentralization at a global level with centralization at the local level
D		4	4	High within cluster and low between clusters	A nearly decomposable system

Figure 5
Mean payoffs for various levels of coupling





(J = Number of clusters)

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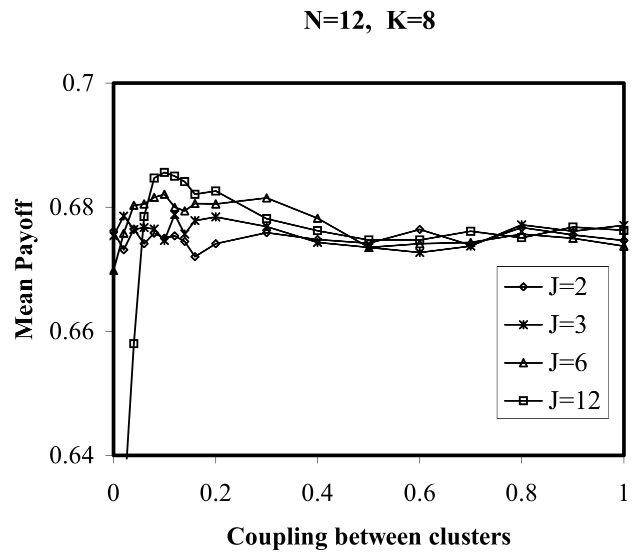
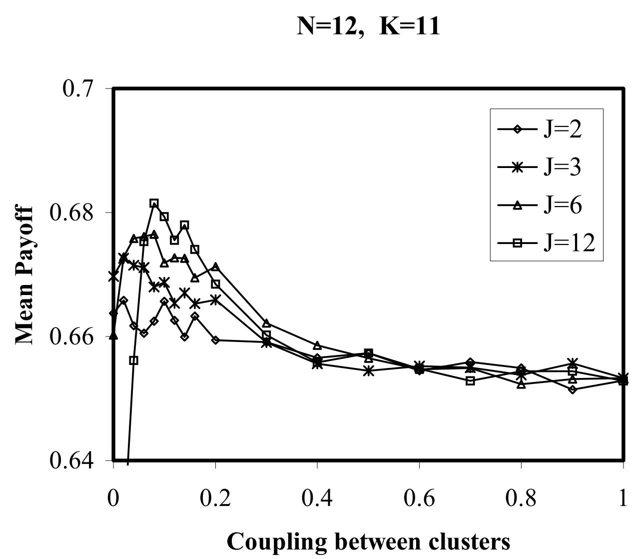
Figure 5 (Contd.)
Mean payoffs for various levels of coupling

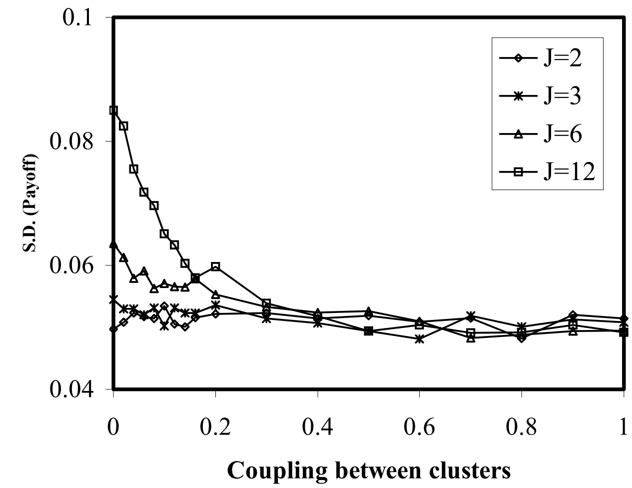




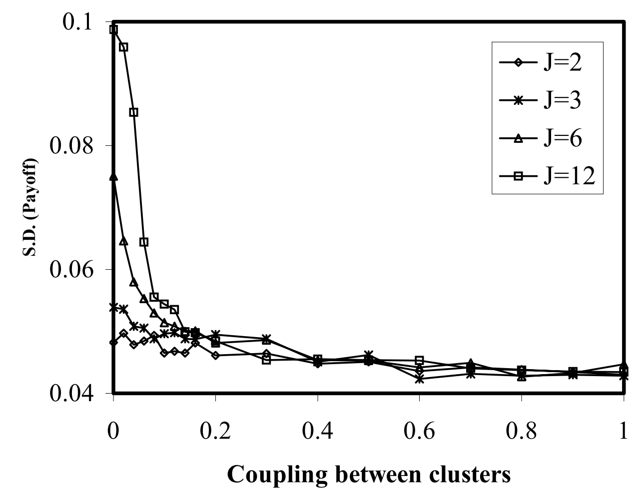
(J = Number of clusters)

Figure 6
Standard deviations of mean payoffs

N=12, K=4



N=12, K=11



(J = Number of clusters)

Figure 7
Payoff of local optimum vs. number of times each local optimum was attained

N=12, K=11

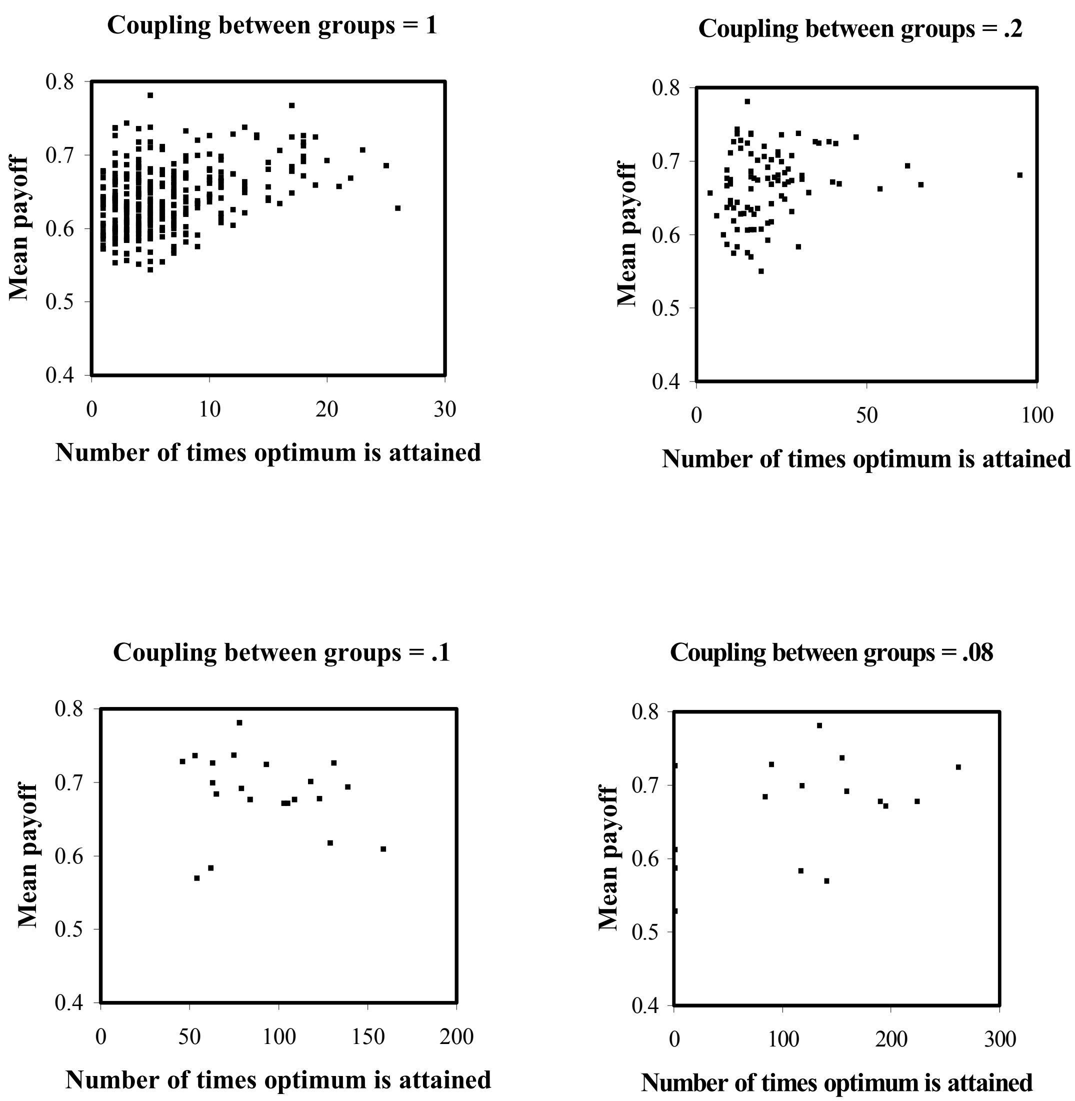
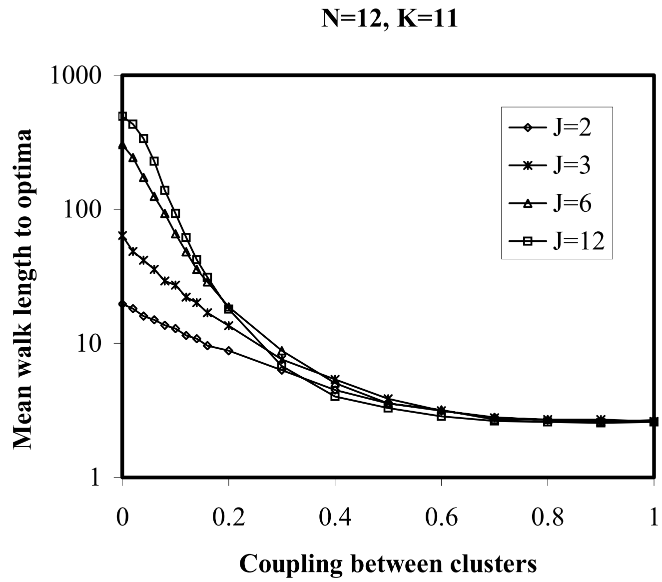


Figure 8
Mean walk length to local optima and percentage of walks that reached local optima

a)



b)

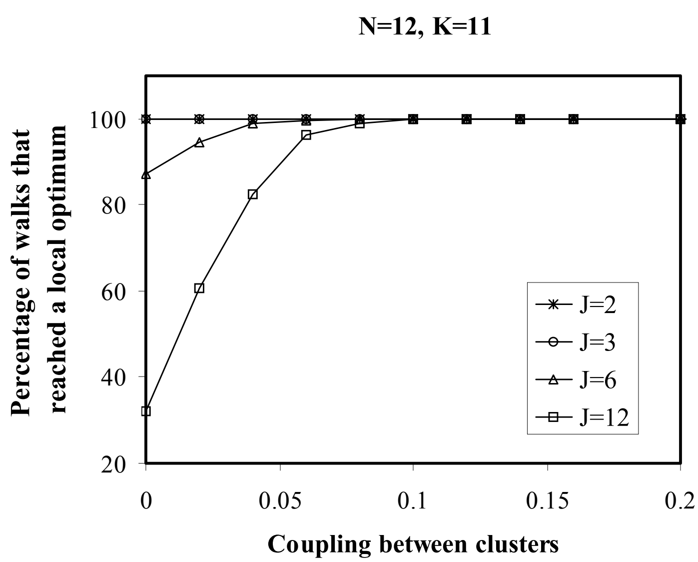
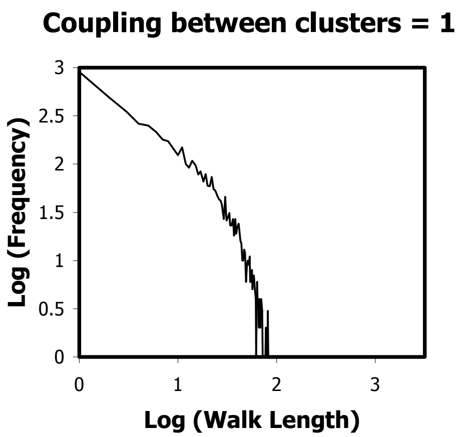


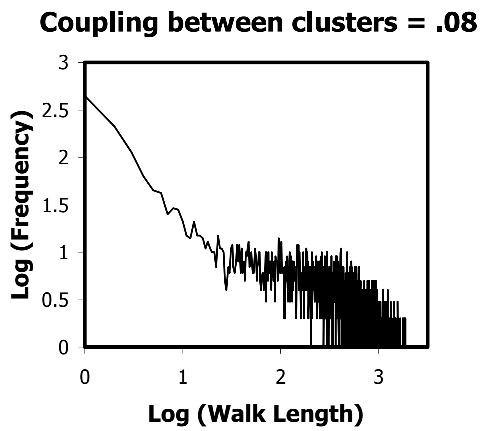
Figure 9
Distribution of walk lengths

N=12, K=11

a)



b)



c)

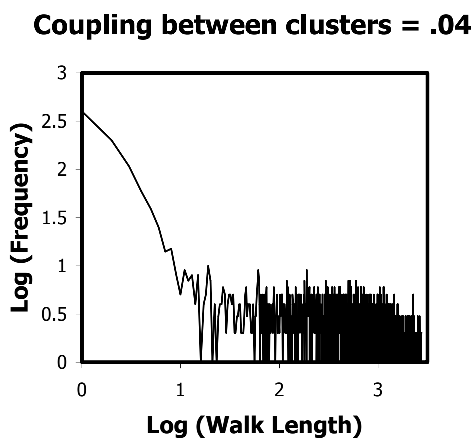


Figure 10
Mean value vs. length of adaptive walk

N=12, K=11

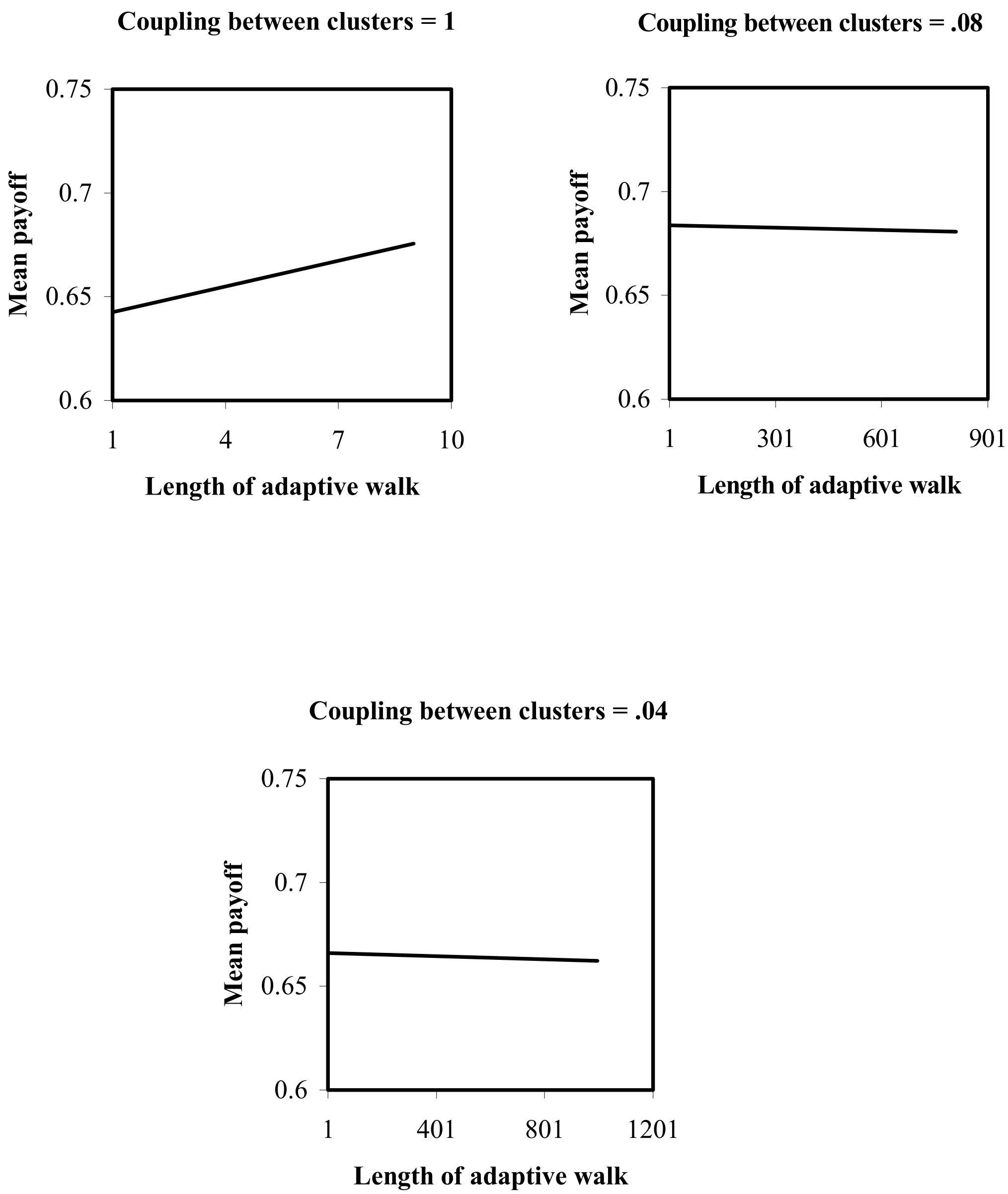
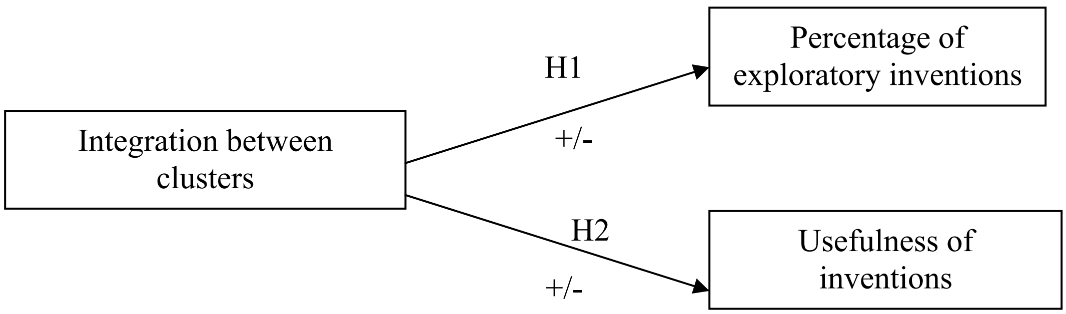


Figure 11
Model of hypothesized relationships

The Structure of a knowledge base

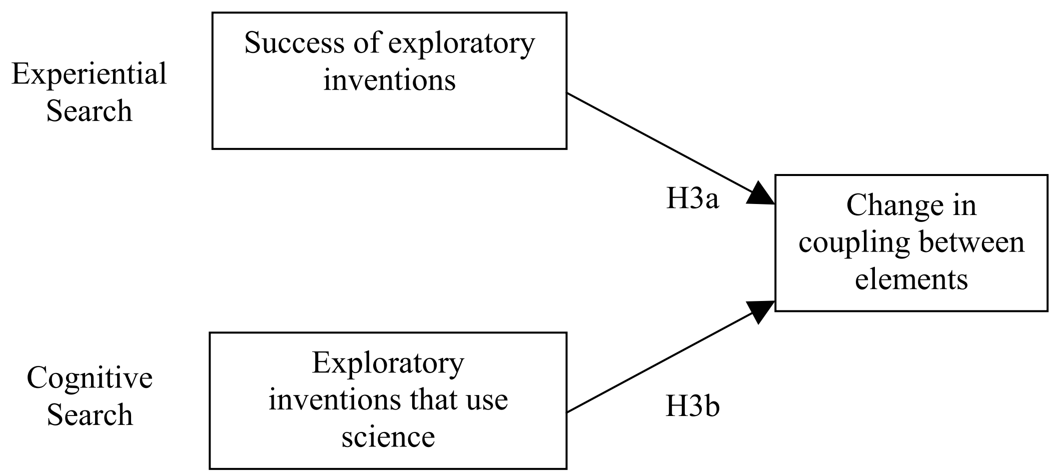


(Continued…)

Figure 11 (Continued)

Changes in the structure of a knowledge base

At the level of the technology-class pairs



At the level of the firm

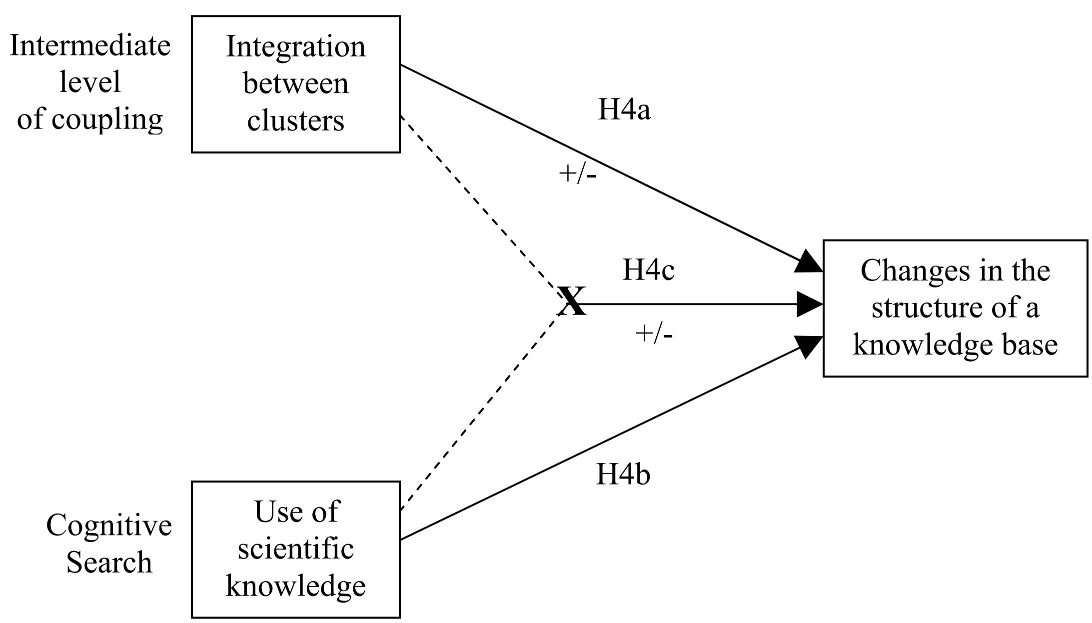
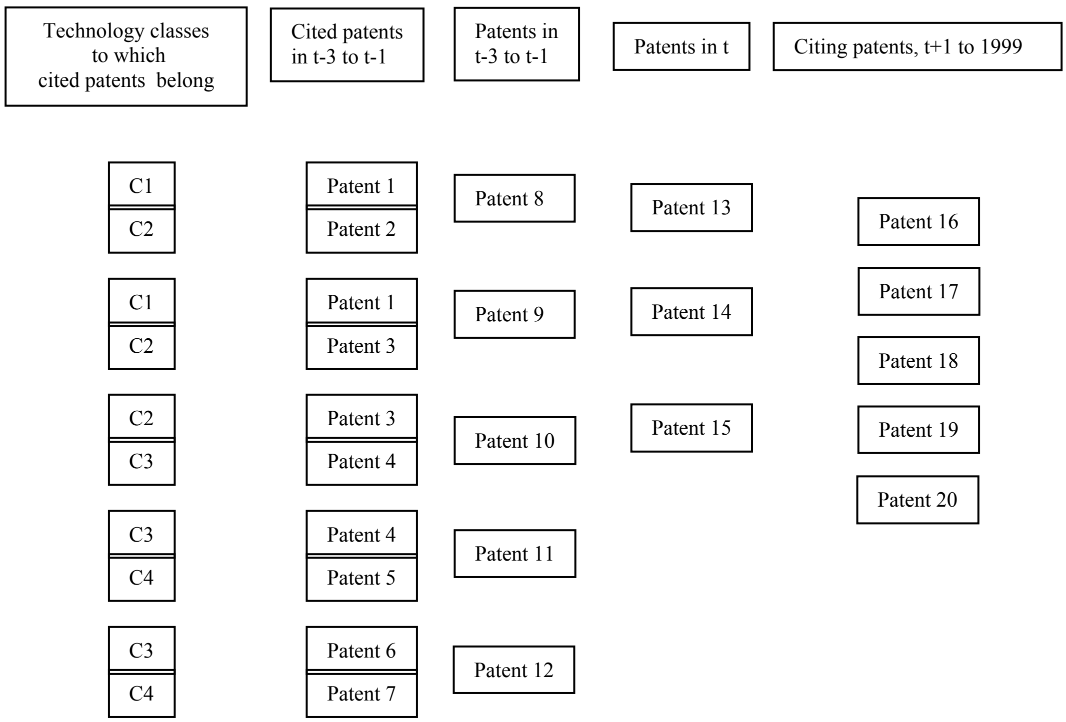


Figure 12
Variable Definitions and Operationalizations



Coupling matrix, L$_{i,\ t\text{-}3\text{ to }t\text{-}1}$

	C1	C2	C3	C4
C1	1			
C2	2/(2+0+1)	1		
C3	0/(0+2+3)	1/(1+2+2)	1	
C4	0/(0+2+2)	0/(0+2+3)	2/(2+0+1)	1

=

	C1	C2	C3	C4
C1	1			
C2	2/3	1		
C3		1/5	1	
C4			2/3	1

Each cell is the similarity between the row technology class and the column technology class measured as the Jaccard's coefficient (Everitt, 1993).

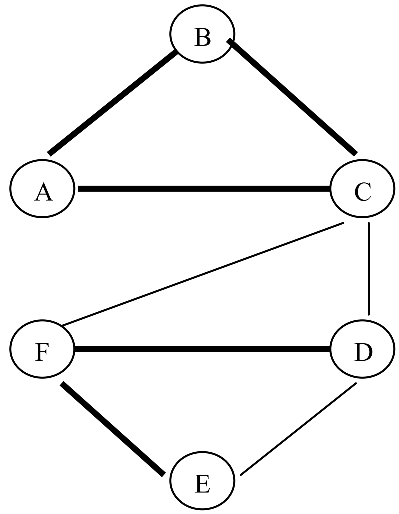
Jaccard's Coefficient = a/(a+b+c)

where a = number of patents in which the two classes are used together
b = number of times class 1 is used, but class 2 is not used
c = number of times class 2 is used, but class 1 is not used

(Continued…)

Figure 12 (Contd.)

Coupling matrix visualized as a network



Nodes represent technology classes
A tie represents coupling between two technology classes
Strength of tie is given by level of coupling

- Dark lines – Strong ties
- Light lines – weak ties

Clustering coefficient

Node	Number of neighbors	Number of possible ties between neighbors	Number of actual ties between neighbors	Clustering $\text{coefficient}_{node}$
A	2	1	1	1
B	2	1	1	1
C	4	6	2	0.33
D	3	3	2	0.66
E	2	1	1	1
F	3	3	2	0.66

Clustering coefficient = Number of actual ties / Number of possible ties between neighbors
= Σ Clustering $\text{coefficient}_{node}$ / number of nodes
= (1+1+0.33+0.66+1+0.66)/6 = 0.78

(Continued…)

Figure 12 (Contd.)

Integration between clusters

1. **Classify ties as weak and strong ties based on a cutoff value.** In the above figure, the ties between node C and node D, between node D and node E and between node C and node F are classified as weak ties while the other ties are classified as strong ties.
2. **For each node identify nodes that are outside its cluster.**
   Method 1: two nodes belong to the same cluster if
   a. They have a strong tie between them and there is at least one common node to which both are tied.
   b. They have a strong tie between them and both nodes do not have any other ties at all
   c. They have a weak tie and there exists at least one node to which both are strongly tied.
   Method 2: Two nodes belong to the same cluster if they have a strong tie
3. **For each node calculate its integration with nodes outside its cluster** as

$$Integration_{node} = \frac{h+w}{\frac{g\times(g-1)}{2}+g}$$

where h = number of neighboring nodes which are outside the focal node's cluster
w = number of ties between neighboring nodes that are outside the focal node's cluster
g = number of all nodes to which focal node is connected such that $\frac{g\times(g-1)}{2}$ is the maximum possible number of ties between the nodes to which focal node is connected.

Node or Tech. Class	Neighbors within cluster	Neighbors outside cluster according to Method 1	Number of neighbors outside cluster, *h*	Number of actual ties between neighbors outside cluster, *w*	Number of possible ties between neighbors + Number of ties, *(g × (g-1))/2 + g*	$Integration_{node}$
A	B,C	-	0	0	1+2=3	(0+0)/3 = 0
B	A,C	-	0	0	1+2=3	(0+0)/3=0
C	A,B	D,F	2	1	6+4=10	(2+1)/10=0.3
D	E,F	C	1	0	3+3=6	(1+0)/6=0.16
E	D,F	-	0	0	1+2=3	(0+0)/3=0
F	D,E	C	1	0	3+3=6	(1+0)/6=0.16

4. $Integration_{i,\, t\text{-}3 \text{ to } t\text{-}1} = \Sigma_j\, Integration_{node\ j} \times$ Number of patents that cite node (or class) j
That is, integration between clusters for firm i is the weighted sum of the integration for each node with the number of patents that cite each class as the weight.

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VITA

Sai Krishna Yayavaram was born in Narasaraopet, India on March 1, 1970, the son of Yayavaram Saraswathi and Yayavaram Sriramamurty. He attended the B.H.P.V. English Medium High School, Visakhapatnam, India till 1985 and Kendriya Vidyalaya, Visakhapatnam, India from 1985 to 1987. He entered the Indian Institute of Technology, Madras, India in 1988 from where he received the degree of Bachelor of Technology in Mechanical Engineering in 1992. He received a Post Graduate Diploma in Management from the Indian Institute of Management, Ahmedabad, India in 1994. During the years 1994-1998 he was employed at Tata Strategic Management Group, Bombay, India. In August 1998, he entered the doctoral program in Management at the University of Texas at Austin.

Permanent Address: 3 Fletcher Circle, Hanover, NH 03755, USA

This dissertation was typed by the author.